

# Analysis of Unicorn Startups

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# 1 Setup

## 1.1 Import Packages

---

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns
import re
```

---

## 1.2 Global Settings

---

```
sns.set_theme(palette='husl', rc={"figure.dpi": 200})
pd.set_option('display.max_columns', 50, 'display.width', 200)
```

---

## 2 Data Processing

### 2.1 Load Data

```
df = pd.read_csv('input/datasets/Unicorns_Completed (2024).csv')
df_wiki = pd.read_csv('input/raw_data/list-of-unicorn-startups_20250619 (wikipedia).csv')
```

---

### 2.2 Data Cleaning

```
def clean_years_to_unicorn_labels(s):
    m = re.match(r'(\d+)y?\s?(\d+)m?o?', s)
    return f'{m[1]}y{m[2]}m' if m else s
df['Years to Unicorn'] = df['Years to Unicorn'].apply(clean_years_to_unicorn_labels)

def correct_industry_labels(s):
    if s == 'Health':
        return 'Healthcare & Life Sciences'
    if s == 'West Palm Beach':
        return 'Enterprise Tech'
    return s
df['Industry'] = df['Industry'].apply(correct_industry_labels)

def correct_company_names(s):
    if s == 'Scale':
        return 'Scale AI'
    return s
df['Company'] = df['Company'].apply(correct_company_names)

# Remove duplicates
df = df[~df.duplicated(['Company'])]
```

---

### 2.3 Data Preparation

#### 2.3.1 Column Types

```
df['Unicorn Date'] = pd.to_datetime(df['Unicorn Date'])
df['Valuation ($B)'] = pd.to_numeric(df['Valuation ($B)'])
df['Valuation ($)'] = df['Valuation ($B)'] * 1e9
df['Unicorn Year'] = df['Unicorn Date'].dt.year
df['Funding ($B)'] = df['Total Equity Funding ($)'] / 1e9
df['Funding ($M)'] = df['Total Equity Funding ($)'] / 1e6
df['Investors'] = df['Select Investors'].str.split(', ')
```

---

#### 2.3.2 Time to Unicorn

```
def convert_years_to_months(years_str):
    if 'y' in years_str and 'm' in years_str:
```

```

    years, months = years_str.split('y')
    months = months.replace('m', '').strip()
    return int(years.strip()) * 12 + int(months)
elif 'y' in years_str:
    years = years_str.replace('y', '').strip()
    return int(years) * 12
elif 'm' in years_str:
    months = years_str.replace('mo', '').replace('m', '').strip()
    return int(months)
else:
    return None
df['Months to Unicorn'] = df['Years to Unicorn'].apply(convert_years_to_months)
df['Years to Unicorn'] = df['Months to Unicorn'] / 12

```

---

### 2.3.3 Merge datasets

- Scraped data from Wikipedia (Latest Valuations, Sectors and Founders)

```

df_wiki.rename(columns={'Valuation (US$ billions)': 'Latest Valuation ($B)',
                       'Industry': 'Sector'},
               inplace=True)
df_wiki = df_wiki.drop_duplicates('Company')
df_wiki['Company'] = df_wiki['Company'].str.strip()
df_wiki['Founder(s)'] = df_wiki['Founder(s)'].str.replace(' and ', ', ')
df_wiki['Founder(s)'] = df_wiki['Founder(s)'].str.split(',')
def list_of_sectors(s):
    sectors = s.replace(' and ', ', ')
    return list(map(lambda x: x.strip().title(), sectors))
df_wiki['Sector'] = df_wiki['Sector'].dropna().apply(list_of_sectors)
df_wiki = df_wiki.assign(tmp_col=lambda x: x.Company.str.lower()) # Create a tmp col
# for Company matching
df = df.assign(tmp_col=lambda x: x.Company.str.lower())\n    .merge(df_wiki[['tmp_col', 'Latest Valuation ($B)', 'Sector', 'Founder(s)']],
           on='tmp_col', how='left')\
    .drop(['tmp_col'], axis=1)
df['Latest Valuation ($B)'] = pd.to_numeric(df['Latest Valuation
                                ($B)'].fillna(value=df['Valuation ($B)']))
# Determine unicorn type based on latest valuations
df['Unicorn Type'] = pd.cut(df['Latest Valuation ($B)'],
                             labels=['Unicorn', 'Decacorn', 'Centicron'],
                             bins=[0, 10, 100, df['Latest Valuation ($B)'].max()])

```

---

## 2.4 Preview

```
df.info()
```

---

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1240 entries, 0 to 1239
```

Data columns (total 20 columns):

#	Column	Non-Null Count	Dtype
0	Company	1240	object
1	Valuation (\$B)	1240	float64
2	Total Equity Funding (\$)	1240	int64
3	Unicorn Date	1240	datetime64[ns]
4	Date Founded	1240	int64
5	Years to Unicorn	1240	float64
6	Industry	1240	object
7	Country	1240	object
8	City	1240	object
9	Select Investors	1240	object
10	Valuation (\$)	1240	float64
11	Unicorn Year	1240	int32
12	Funding (\$B)	1240	float64
13	Funding (\$M)	1240	float64
14	Investors	1240	object
15	Months to Unicorn	1240	int64
16	Latest Valuation (\$B)	1240	float64
17	Sector	427	object
18	Founder(s)	137	object
19	Unicorn Type	1240	category

dtypes: category(1), datetime64[ns](1), float64(6), int32(1), int64(3), object(8)  
memory usage: 180.7+ KB

## 3 Exploratory Data Analysis

### 3.1 Industry-Based Analysis

#### 3.1.1 Distribution of Companies across Different Industries

---

```
_df = df.groupby('Industry').size()
_df
```

---

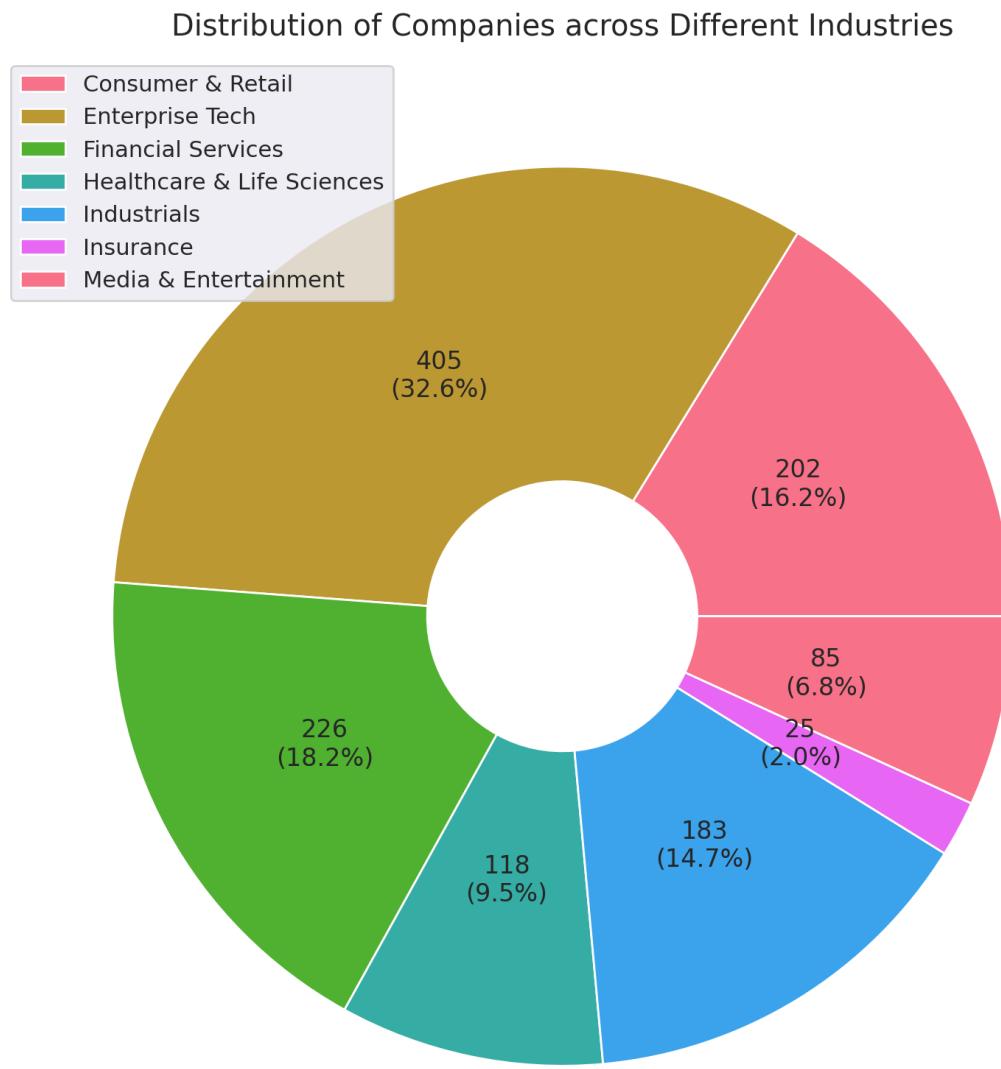
Industry	
Consumer & Retail	202
Enterprise Tech	405
Financial Services	226
Healthcare & Life Sciences	118
Industrials	183
Insurance	25
Media & Entertainment	85

```
dtype: int64
```

---

```
fig, ax = plt.subplots(figsize=(12,8), constrained_layout=True)
total = _df.sum()
_df.plot.pie(legend=True, labels=None,
             autopct=lambda pct:f"\n{round(total*pct/100)}\n({pct:.1f}%)",
             wedgeprops=dict(width=0.7, edgecolor='w'))
plt.suptitle('Distribution of Companies across Different Industries')
plt.show()
```

---



### 3.1.2 Distribution of Valuation across Different Industries

---

```
_df = df.groupby('Industry')['Latest Valuation ($B)'].sum().sort_values(ascending=False)

fig = plt.figure(figsize=(12, 6))
gs = fig.add_gridspec(nrows=2, ncols=2)
```

```

ax1 = fig.add_subplot(gs[0, 0])
ax2 = fig.add_subplot(gs[0, 1])
ax1.sharey(ax2)
# ax3 = fig.add_subplot(gs[1, :])

g = sns.barplot(y=_df.index, x=_df.values, hue=_df.index, ax=ax1)
for i in ax1.containers:
    ax1.bar_label(i, fmt='%.2f')
ax1.set_xlabel('Total Valuation ($B)')
ax1.set_ylabel(None)
sns.boxplot(df, y='Industry', x='Latest Valuation ($B)', hue='Industry', showfliers=False,
            ax=ax2)
ax2.get_yaxis().set_visible(False)
ax2.set_xlabel('Mean Valuation ($B)')

plt.grid(axis='x', alpha=0.75)
plt.suptitle('Distribution of Valuation across Different Industries')

plt.ylabel(None)
plt.show()

```

---

Distribution of Valuation across Different Industries



### 3.1.3 Distribution of Equity Funding across Different Industries

---

```

_df = df.groupby('Industry')['Funding ($B)'].sum().sort_values(ascending=False)

fig = plt.figure(figsize=(12, 6))
gs = fig.add_gridspec(nrows=2, ncols=2)

ax1 = fig.add_subplot(gs[0, 0])
ax2 = fig.add_subplot(gs[0, 1])
ax1.sharey(ax2)

g = sns.barplot(y=_df.index, x=_df.values, hue=_df.index, ax=ax1)
for i in ax1.containers:
    ax1.bar_label(i, fmt='%.2f')
ax1.set_xlabel('Total Equity Funding ($B)')
ax1.set_ylabel(None)
sns.boxplot(df, y='Industry', x='Funding ($M)', hue='Industry', showfliers=False, ax=ax2)
ax2.get_yaxis().set_visible(False)
ax2.set_xlabel('Mean Equity Funding ($M)')

```

```

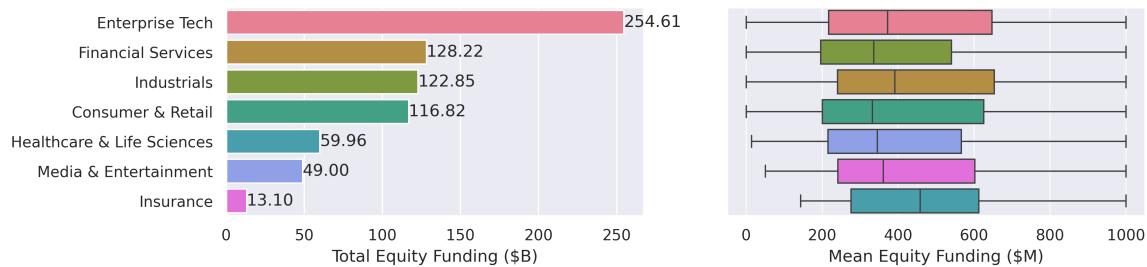
plt.grid(axis='x', alpha=0.75)
plt.suptitle('Distribution of Equity Funding across Different Industries')

plt.ylabel(None)
plt.show()

```

---

Distribution of Equity Funding across Different Industries



## 3.2 Geographical Analysis

### 3.2.1 Top Countries by Valuation

```

_df = df.groupby('Country')['Latest Valuation ($B)']\ 
    .agg(['count', 'sum'])\ 
    .sort_values(by='sum', ascending=False)\ 
    .head(30)

fig, ax = plt.subplots(2, 1, figsize=(12, 8), sharex=True, gridspec_kw={'height_ratios': [2, 1]})

g = sns.barplot(_df, x=_df.index, y='sum', hue=_df.index, ax=ax[0])
g.set(ylabel='Latest Valuation ($B)', 
     yscale='log')
for i in ax[0].containers:
    ax[0].bar_label(i, rotation=45, fontsize=8)

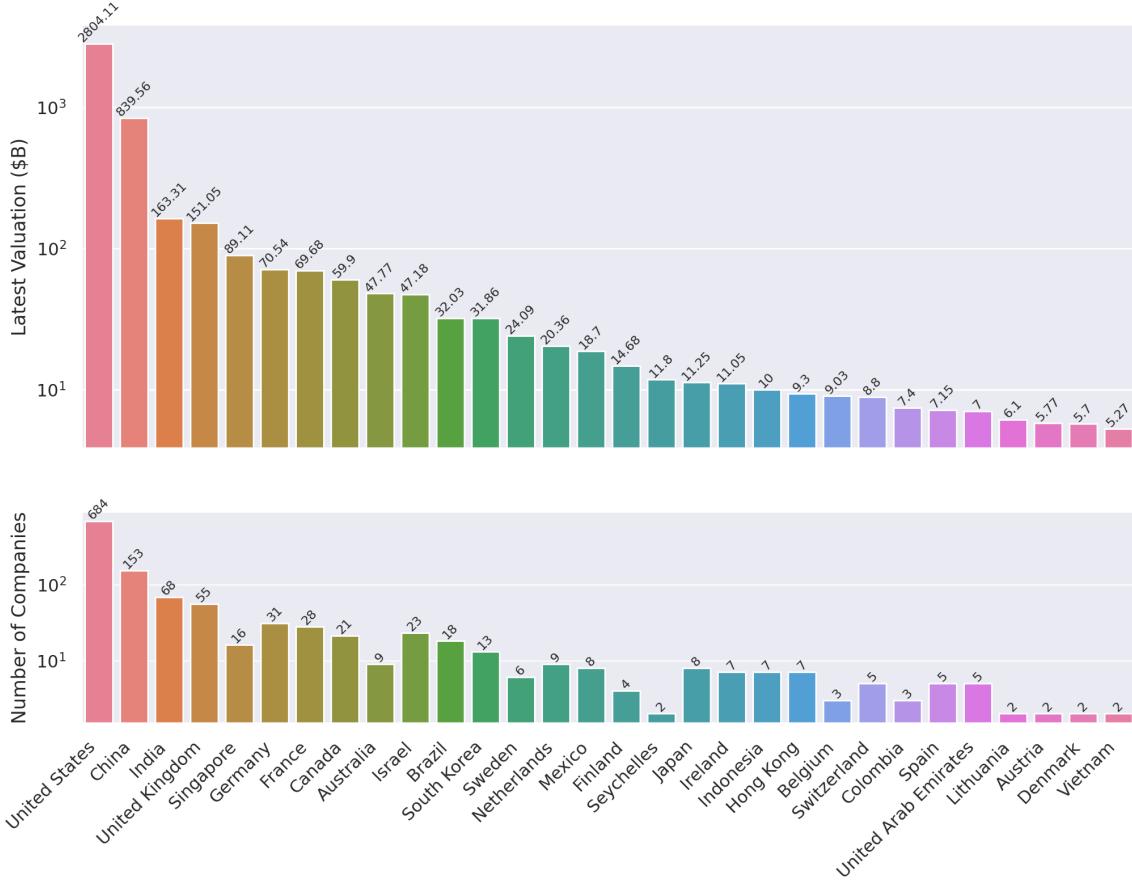
g = sns.barplot(_df, x=_df.index, y='count', hue=_df.index, ax=ax[1])
g.set(ylabel='Number of Companies', 
     yscale='log')
for i in ax[1].containers:
    ax[1].bar_label(i, rotation=45, fontsize=8)

plt.suptitle('Top Countries')
plt.grid(axis='y', alpha=0.75)
plt.xticks(rotation=45, ha='right')
plt.xlabel(None)
plt.show()

```

---

## Top Countries



### 3.2.2 Top Countries across Different Industries

```

df_filtered = df[df['Country'].isin(top_countries.head(10).index)]\ 
    .groupby(['Country', 'Industry'])['Latest Valuation ($B)']\ 
    .agg(['count', 'sum'])\ 
    .reset_index()

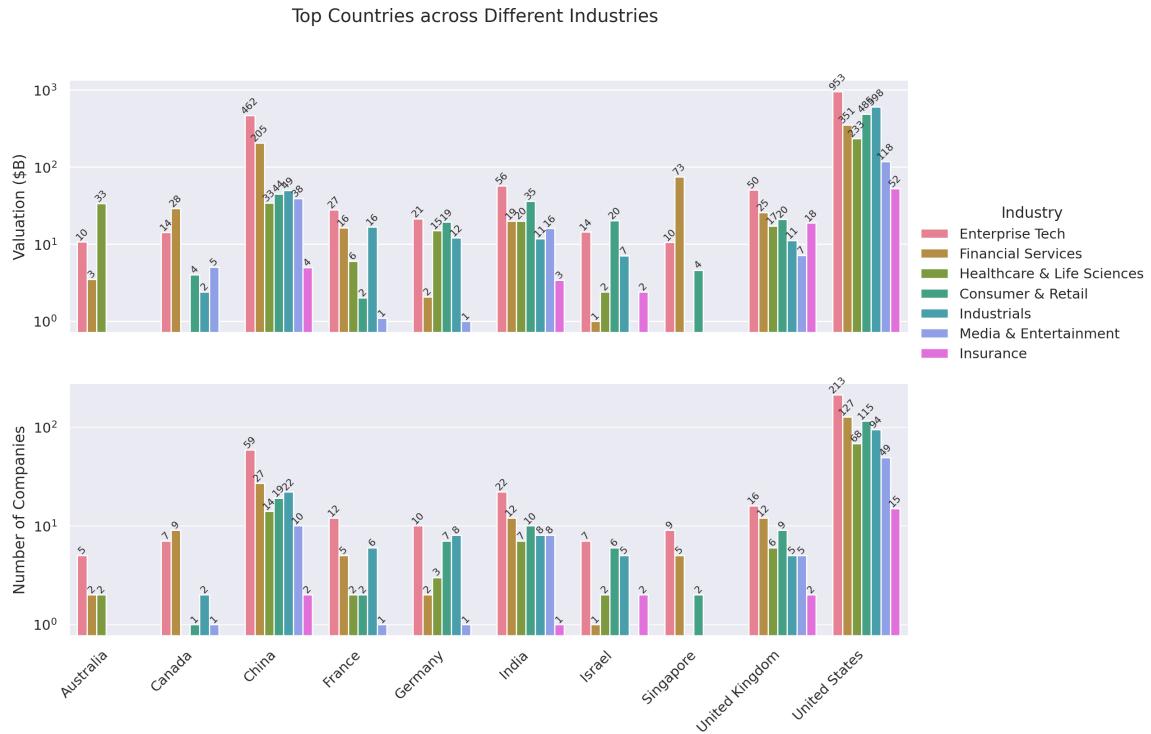
fig, ax = plt.subplots(2, 1, figsize=(12, 8), sharex=True)
g = sns.barplot(df_filtered, x='Country', y='sum', hue='Industry', ax=ax[0])
sns.move_legend(ax[0], 'upper left', bbox_to_anchor=(1, .55), frameon=False)
g.set(ylabel='Valuation ($B)', 
      yscale='log')
for i in ax[0].containers:
    ax[0].bar_label(i, rotation=45, fontsize=8, fmt='%d')
g = sns.barplot(df_filtered, x='Country', y='count', hue='Industry', ax=ax[1], 
                legend=False)
g.set(ylabel='Number of Companies', 
      yscale='log')
for i in ax[1].containers:
    ax[1].bar_label(i, rotation=45, fontsize=8)
plt.suptitle('Top Countries across Different Industries')
plt.grid(axis='y', alpha=0.75)

```

```

plt.xticks(rotation=45, ha='right')
plt.xlabel(None)
plt.show()

```



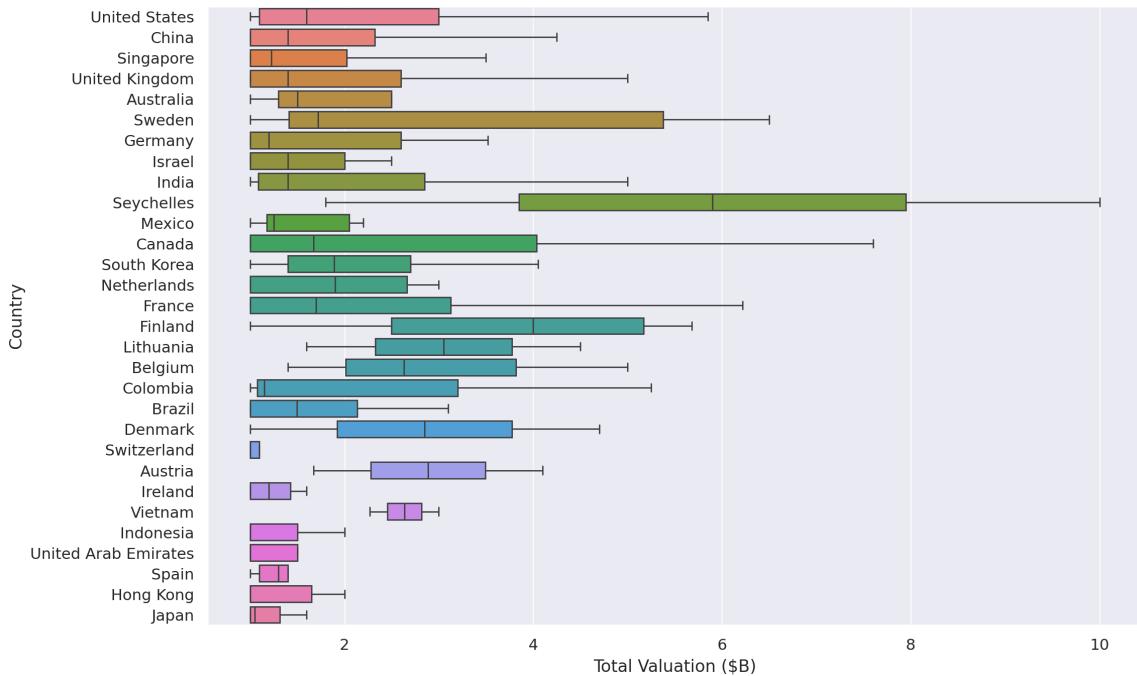
### 3.2.3 Mean Distribution of Valuations across Different Countries

```

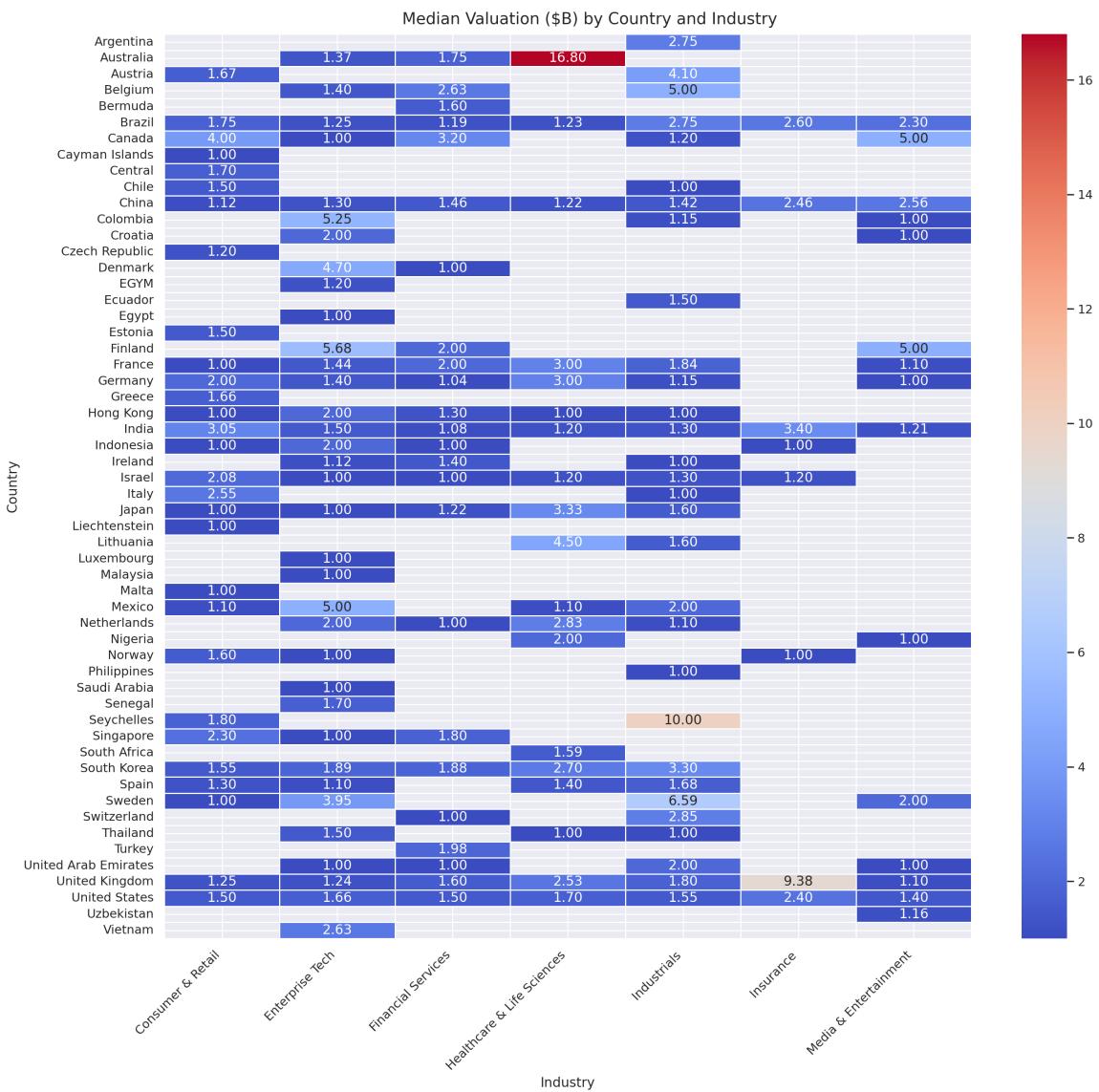
fig, ax = plt.subplots(figsize=(12, 8))
sns.boxplot(df[df['Country'].isin(top_countries.index)],
            y='Country',
            x='Latest Valuation ($B)',
            hue='Country',
            showfliers=False)
plt.suptitle('Distribution of Valuations across Different Countries')
ax.set(xlabel='Total Valuation ($B)',
       ylabel='Country')
plt.grid(axis='x', alpha=0.7)
plt.show()

```

Distribution of Valuations across Different Countries



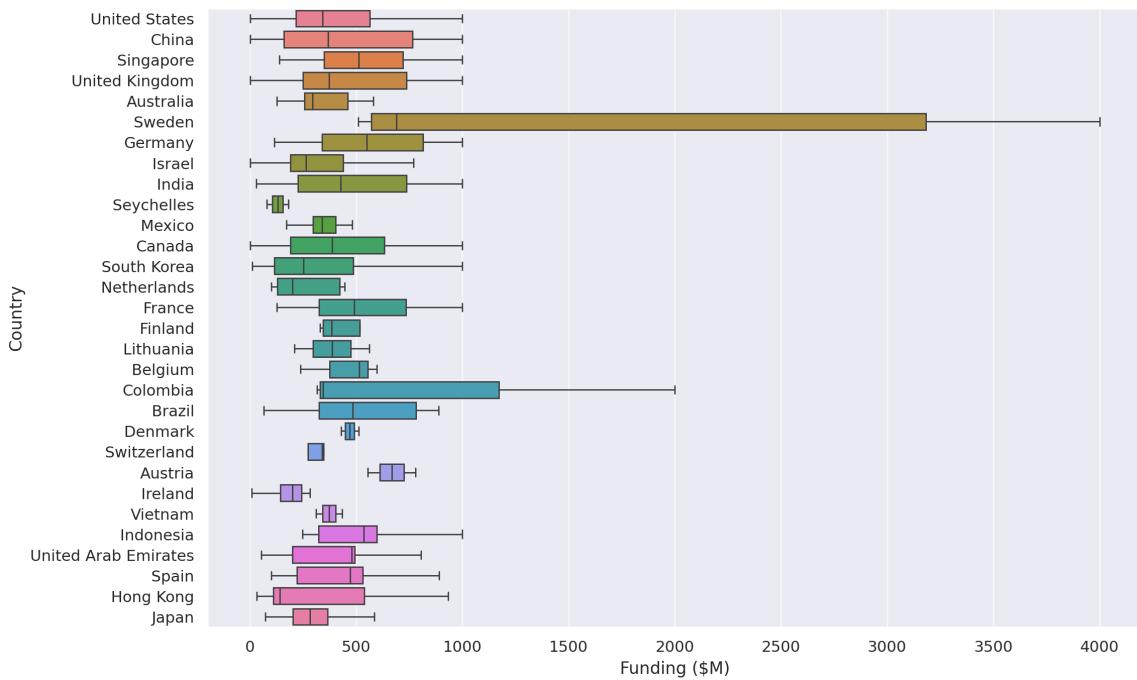
```
_df = df.pivot_table(index='Country', columns='Industry', values='Latest Valuation ($B)',  
                     aggfunc='median')  
plt.figure(figsize=(15, 14))  
sns.heatmap(_df, cmap='coolwarm', annot=True, fmt=".2f", linewidths=0.5)  
plt.xticks(rotation=45, ha='right')  
plt.suptitle('Median Valuation ($B) by Country and Industry')  
plt.tight_layout()  
plt.show()
```



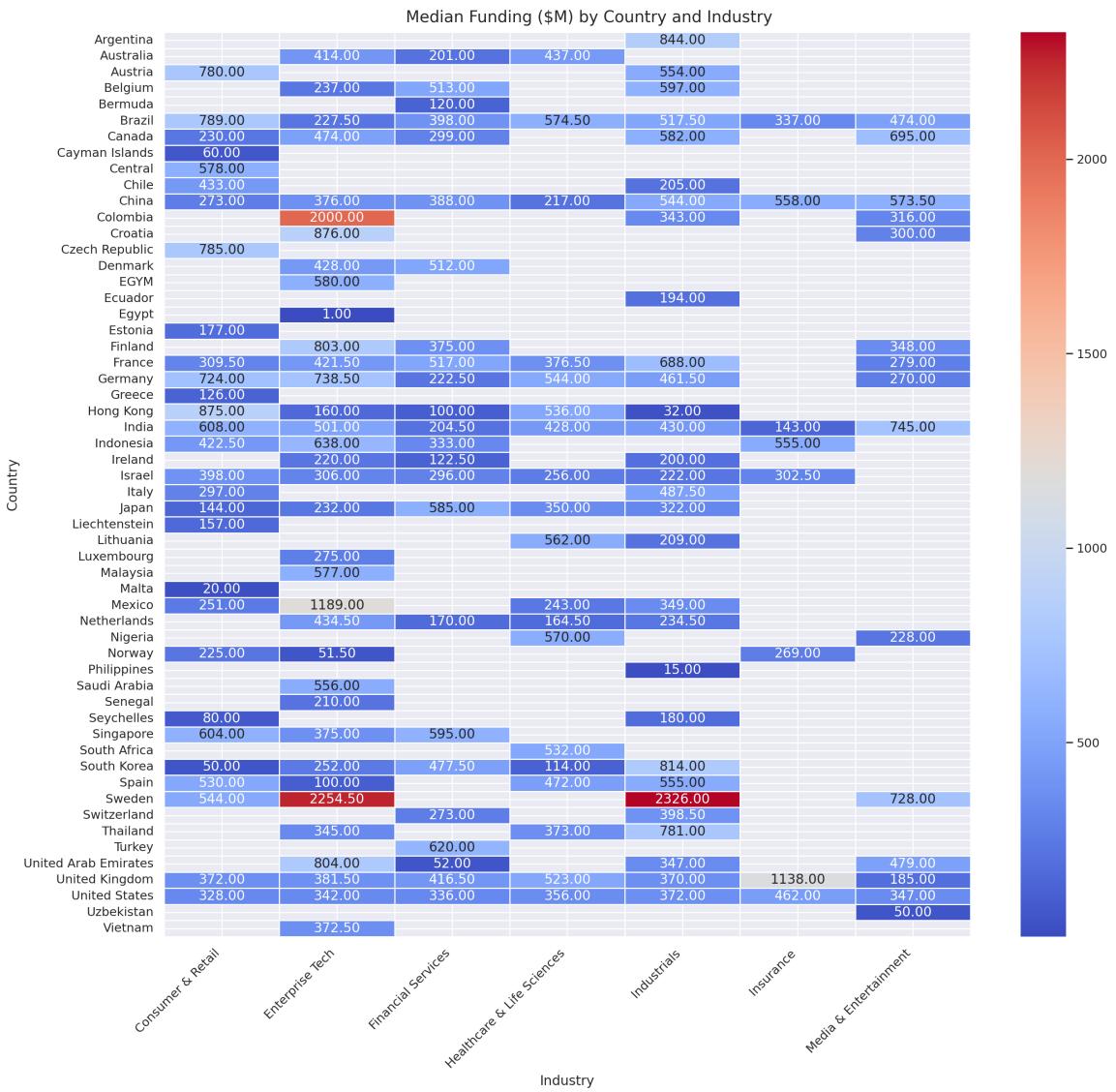
### 3.2.4 Mean Distribution of Equity Funding across Different Countries

```
fig, ax = plt.subplots(figsize=(12,8))
sns.boxplot(df[df['Country'].isin(top_countries.index)], y='Country', x='Funding ($M)',
            hue='Country', showfliers=False)
plt.suptitle('Distribution of Funding across Different Countries')
ax.set(xlabel='Funding ($M)',
       ylabel='Country')
plt.grid(axis='x', alpha=0.7)
plt.show()
```

Distribution of Funding across Different Countries



```
_df = df.pivot_table(index='Country', columns='Industry', values='Funding ($M)',  
                     aggfunc='median')  
plt.figure(figsize=(15, 14))  
sns.heatmap(_df, cmap='coolwarm', annot=True, fmt=".2f", linewidths=0.5)  
plt.xticks(rotation=45, ha='right')  
plt.suptitle('Median Funding ($M) by Country and Industry')  
plt.tight_layout()  
plt.show()
```



### 3.3 Sector-Based Analysis

#### 3.3.1 Top Sectors

```

_df = df.explode('Sector')[['Sector', 'Latest Valuation ($B)', 'Funding ($B)']]\
    .groupby('Sector')[['Latest Valuation ($B)', 'Funding ($B)']]\
    .agg({'Latest Valuation ($B)': ['sum', 'count'], 'Funding ($B)': 'sum'})
_df.columns = ['Valuation ($B)', 'Number of Companies', 'Funding ($B)']
_df = _df.sort_values(by='Valuation ($B)', ascending=False).head(20)
print(_df)

```

Sector	Valuation (\$B)	Number of Companies	Funding (\$B)
Artificial Intelligence	591.48	23	49.843
Aerospace	354.20	2	10.000
Internet	320.00	4	9.373

Software	214.06	44	35.165
Financial Technology	185.27	53	34.698
E-Commerce	169.11	22	23.460
Financial Services	142.55	14	21.798
Cybersecurity	54.08	21	12.301
Marketplace	48.03	14	13.480
Cryptocurrency	41.90	11	4.204
Video Games	39.70	4	9.375
Educational Technology	33.47	9	9.586
Transportation	33.45	8	12.480
Graphic Design	33.00	2	0.775
Software As A Service	32.70	11	4.542
Healthcare	31.30	11	6.196
Collaborative Software	24.00	2	1.400
Finance	21.30	4	2.359
Blockchain	20.80	4	2.060
Logistics	18.02	9	6.418

---

```

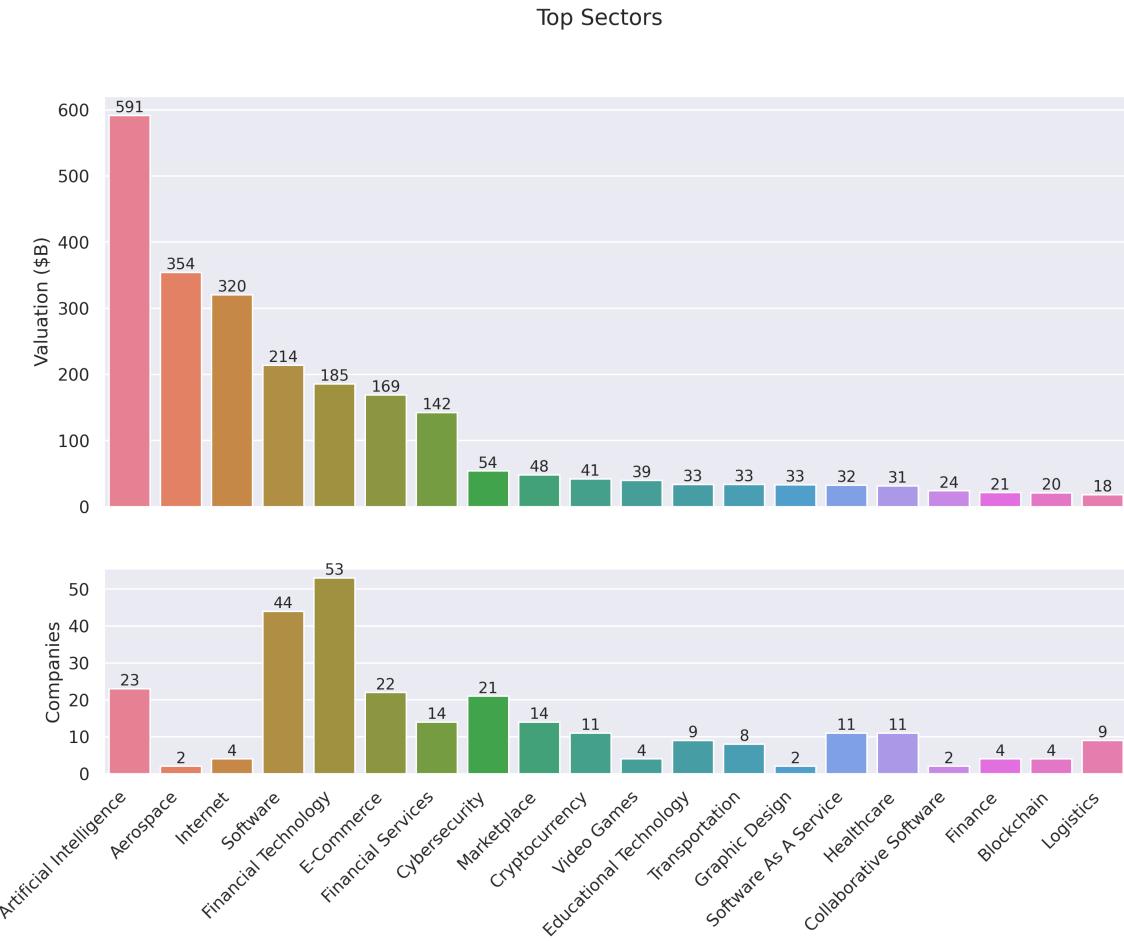
fig, ax = plt.subplots(2, 1, figsize=(12, 8), dpi=DPI, sharex=True,
→  gridspec_kw={'height_ratios': [2, 1]})

g = sns.barplot(_df, x=_df.index, y='Valuation ($B)', ax=ax[0], hue=_df.index)
for i in ax[0].containers:
    g.bar_label(i, fmt='%d', fontsize=10)

# g = sns.barplot(_df, x=_df.index, y='Funding ($B)', ax=ax[1], hue=_df.index)
# for i in ax[1].containers:
#     g.bar_label(i, fmt='%.1f', fontsize=10)
g = sns.barplot(_df, x=_df.index, y='Number of Companies', ax=ax[1], hue=_df.index)
ax[1].set(ylabel='Companies')
for i in ax[1].containers:
    g.bar_label(i, fmt='%d', fontsize=10)
plt.xticks(rotation=45, ha='right')
plt.xlabel(None)
plt.suptitle('Top Sectors')
plt.show()

```

---



## 3.4 Company-Based Analysis

### 3.4.1 Top Companies by Valuation

```
top_companies = df.sort_values(by='Latest Valuation ($B)', ascending=False).head(20)
top_companies['Growth Rate'] = (top_companies['Latest Valuation ($B)'] -
→ top_companies['Valuation ($B)']) / top_companies['Valuation ($B)'] * 100
```

```
# Set the positions and width for the bars
N = len(top_companies)
ind = np.arange(N) # the x locations for the groups
width = 0.35 # the width of the bars

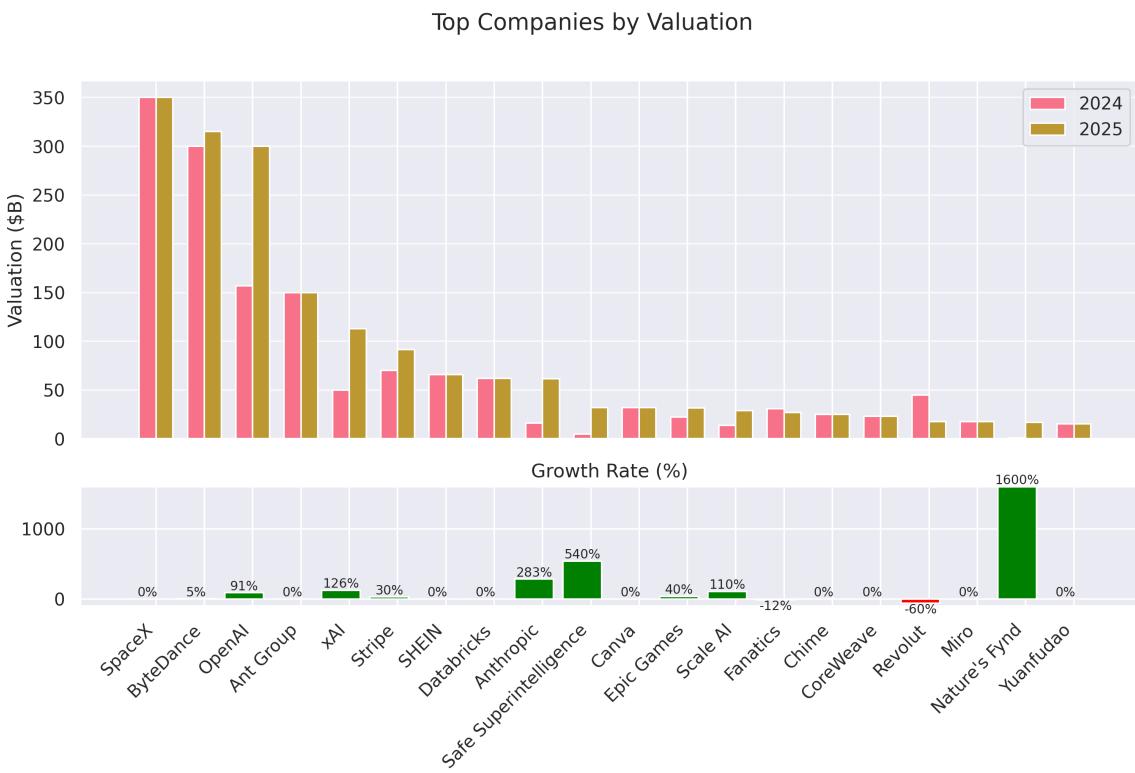
# Create the bars for valuation and funding
fig, ax = plt.subplots(2, 1, figsize=(12, 6), dpi=DPI, gridspec_kw={'height_ratios': [3,
→ 1]}, sharex=True)
ax[0].bar(ind, top_companies['Valuation ($B)'], width, label='2024')
ax[0].bar(ind + width, top_companies['Latest Valuation ($B)'], width, label='2025')

ax[0].set(ylabel='Valuation ($B)')
ax[0].legend()
ax[0].grid(axis='y', alpha=0.75)
```

```

ax[1].bar(ind, top_companies['Growth Rate'], color=np.where(top_companies['Growth
→  Rate']>0, 'g', 'r'))
ax[1].set(title='Growth Rate (%)')
for i in ax[1].containers:
    ax[1].bar_label(i, fmt='%d%%', fontsize=8)
ax[1].set(ylim=(-100,1600))
plt.xticks(ind+width/2, top_companies['Company'], rotation=45, ha='right')
plt.suptitle('Top Companies by Valuation')
plt.show()

```



## Top Companies across Different Industries

```

_df = df.groupby('Industry')[['Company', 'Latest Valuation ($B)']].apply(lambda grp:
→  grp.nlargest(3, 'Latest Valuation ($B)')[['Company', 'Latest Valuation ($B)']]
_df.index = _df.index.droplevel(1)
_df = _df.groupby(level=0).apply(lambda x: ,
→  .join(x['Company'])).reset_index(name='Companies')
_df

```

Industry	Companies
0 Consumer & Retail	xAI, Stripe, Safe Superintelligence
1 Enterprise Tech	SpaceX, ByteDance, Anthropic
2 Financial Services	Ant Group, SHEIN, Epic Games
3 Healthcare & Life Sciences	Canva, CoreWeave, Miro
4 Industrials	OpenAI, Databricks, Discord
5 Insurance	Revolut, Gusto, Ramp
6 Media & Entertainment	Nature's Fynd, Xingsheng Selected, Talkdesk

## Top Companies accross Different Countries

---

```

_df = df[df['Country'].isin(top_countries.index)]\ 
    .groupby('Country')[['Company', 'Latest Valuation ($B)']]\
    .apply(lambda grp: grp.nlargest(3, 'Latest Valuation ($B)').[['Company', 'Latest
    ~ Valuation ($B)']])
_df.index = _df.index.droplevel(1)
_df = _df.groupby(level=0)\ 
    .apply(lambda x: ', '.join(x['Company']))\
    .reset_index(name='Companies')
_df

```

---

	Country	Companies
0	Australia	Canva, Airwallex, Immutable
1	Austria	BitPanda, GoStudent
2	Belgium	Collibra, Odoo, Deliverect
3	Brazil	QuintoAndar, Nuvemshop, Wildlife Studios
4	Canada	Dapper Labs, 1Password, Cohere
5	China	ByteDance, Ant Group, Yuanfudao
6	Colombia	Rappi, LifeMiles, Habi
7	Denmark	Pleo, Lunar
8	Finland	RELEX, Oura, Aiven
9	France	Doctolib, Mistral AI, Back Market
10	Germany	Celonis, Personio, Helsing
11	Hong Kong	Babel Finance, Trendy Group International, HashKeyHashKey
12	India	BYJU's, OYO Rooms, Dream11
13	Indonesia	Traveloka, Akulaku, eFishery
14	Ireland	BrowserStack, Wayflyer, Flipdish
15	Israel	StarkWare, Wiz, Moon Active
16	Japan	Preferred Networks, SmartHR, Spiber
17	Lithuania	Vinted, Nord Security
18	Mexico	Kavak, Bitso, Clip
19	Netherlands	Mollie, MessageBird, BackBase
20	Seychelles	KuCoin, Scroll
21	Singapore	SHEIN, HyalRoute, Coda Payments
22	South Korea	Toss, Yello Mobile, Kurly
23	Spain	Jobandtalent, Cabify, TravelPerk
24	Sweden	Northvolt, Klarna, Kry
25	Switzerland	SonarSource, Nexthink, MindMaze
26	United Arab Emirates	Vista Global, Tabby, Kitopi
27	United Kingdom	Revolut, Global Switch, Checkout.com
28	United States	SpaceX, OpenAI, xAI
29	Vietnam	Sky Mavis, MoMo

## Top Companies accross Different Sectors

---

```
top_sectors = df.explode('Sector')\n    .groupby('Sector')['Latest Valuation ($B)']\n    .sum()\n    .sort_values(ascending=False)\n    .head(30)\n\n_df = df.explode('Sector')\n_df = _df[_df['Sector'].isin(top_sectors.index)]\n    .groupby('Sector')[['Company', 'Latest Valuation ($B)']]\\n    .apply(lambda grp: grp.nlargest(3, 'Latest Valuation ($B)'))[['Company', 'Latest\n    ~ Valuation ($B)']]\\n\n_df.index = _df.index.droplevel(1)\n_df = _df.groupby(level=0)\\n    .apply(lambda x: ', '.join(x['Company']))\\n    .reset_index(name='Companies')\n\n_df
```

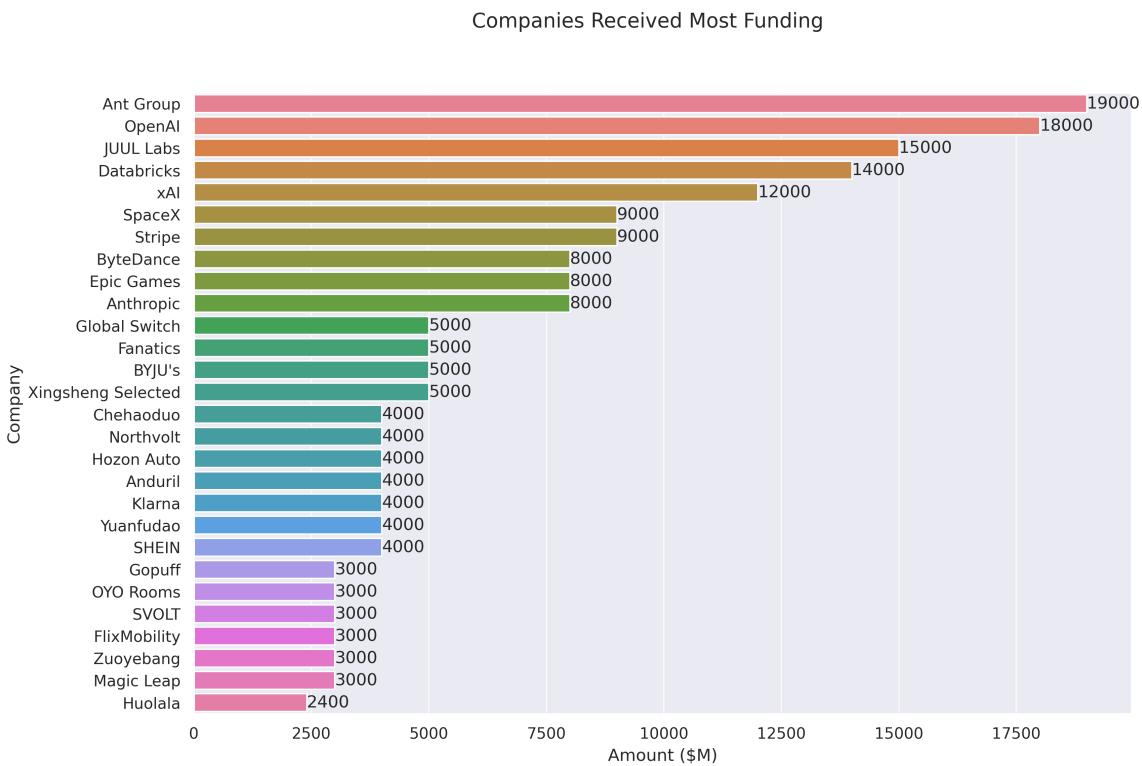
---

	Sector	Companies
0	Aerospace	SpaceX, Relativity Space
1	Artificial Intelligence	OpenAI, xAI, Anthropic
2	Batteries	Northvolt
3	Blockchain	Alchemy, Chainalysis, ConsenSys
4	Collaborative Software	Grammarly, Airtable
5	Consumer Packaged Goods	Nature's Fynd
6	Cryptocurrency	Ripple, KuCoin, Blockchain.com
7	Cybersecurity	Tanium, Wiz, OneTrust
8	E-Commerce	SHEIN, Fanatics, Gopuff
9	Educational Technology	Yuanfudao, Articulate, Unacademy
10	Fantasy Sports	Dream11, Sorare
11	Finance	Brex, Qonto, TradingView
12	Financial Services	Stripe, Chime, Airwallex
13	Financial Technology	Revolut, Plaid, GoodLeap
14	Graphic Design	Canva, PicsArt
15	Health Technology	Ro, Commure, Alan
16	Healthcare	Devoted Health, Noom, Hinge Health
17	Internet	ByteDance, Automattic, InMobi
18	Logistics	Flexport, Zipline, Cart.com
19	Marketplace	Chehaoduo, Kavak, Back Market
20	Retail	HEYTEA, Lenskart, Away
21	Robotics	Nuro, CMR Surgical, Exotec
22	Self-Driving Cars	ZongMu Technology
23	Software	Databricks, Miro, Discord
24	Software As A Service	Talkdesk, ContentSquare, Postman
25	Software Development	OutSystems, Unqork, Lightricks
26	Technology	MEGVII, MURAL, Workato
27	Transportation	Bolt, Bolt, Rappi
28	Video Games	Epic Games, Niantic, Sky Mavis
29	Workforce Management	Rippling, Papaya Global, Workrise

### 3.4.2 Most-Funded Companies

```
df_filtered = df[df['Funding ($M)'] > 2000].sort_values(by='Funding ($M)',  
→ ascending=False).head(30)
```

```
plt.subplots(figsize=(12, 8), dpi=300)  
ax = sns.barplot(df_filtered, y='Company', x='Funding ($M)', hue='Company')  
for i in ax.containers:  
    ax.bar_label(i)  
plt.suptitle('Companies Received Most Funding')  
plt.xlabel('Amount ($M)')  
plt.grid(axis='x', alpha=0.75)  
plt.show()
```



### 3.4.3 Distribution of Valuation by Companies

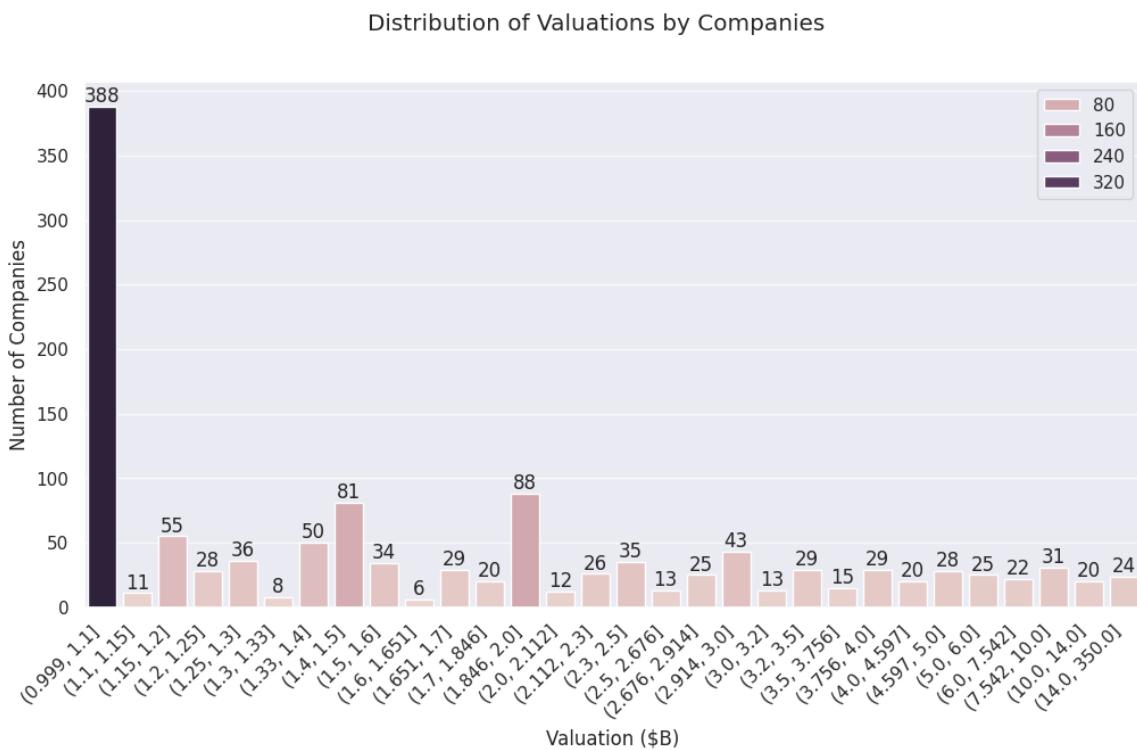
```
# Define the bins for valuation ranges  
# bins = [0, 1, 1.5, 2, 3, 4, 5, 6, 8, 10, 20, 30, 50, 100, 200, 300, 400]  
# labels = [f'{a}-{b}' for a, b in zip(bins[:-1], bins[1:])]  
# cuts = pd.cut(df['Valuation ($B)'], bins=bins, labels=labels)  
  
cuts = pd.qcut(df['Latest Valuation ($B)'], 50, duplicates='drop')  
  
# Count the number of companies in each bin  
distribution = cuts.value_counts().sort_index()  
  
# Plot the Bar Chart
```

```

plt.figure(figsize=(12, 6))
ax = sns.barplot(x=distribution.index,
                  y=distribution.values, hue=distribution.values)
for i in ax.containers:
    ax.bar_label(i)
plt.suptitle('Distribution of Valuations by Companies')
plt.xlabel('Valuation ($B)')
plt.ylabel('Number of Companies')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', alpha=0.75)
plt.show()

```

---



### 3.4.4 Distribution of Equity Funding by Companies

---

```

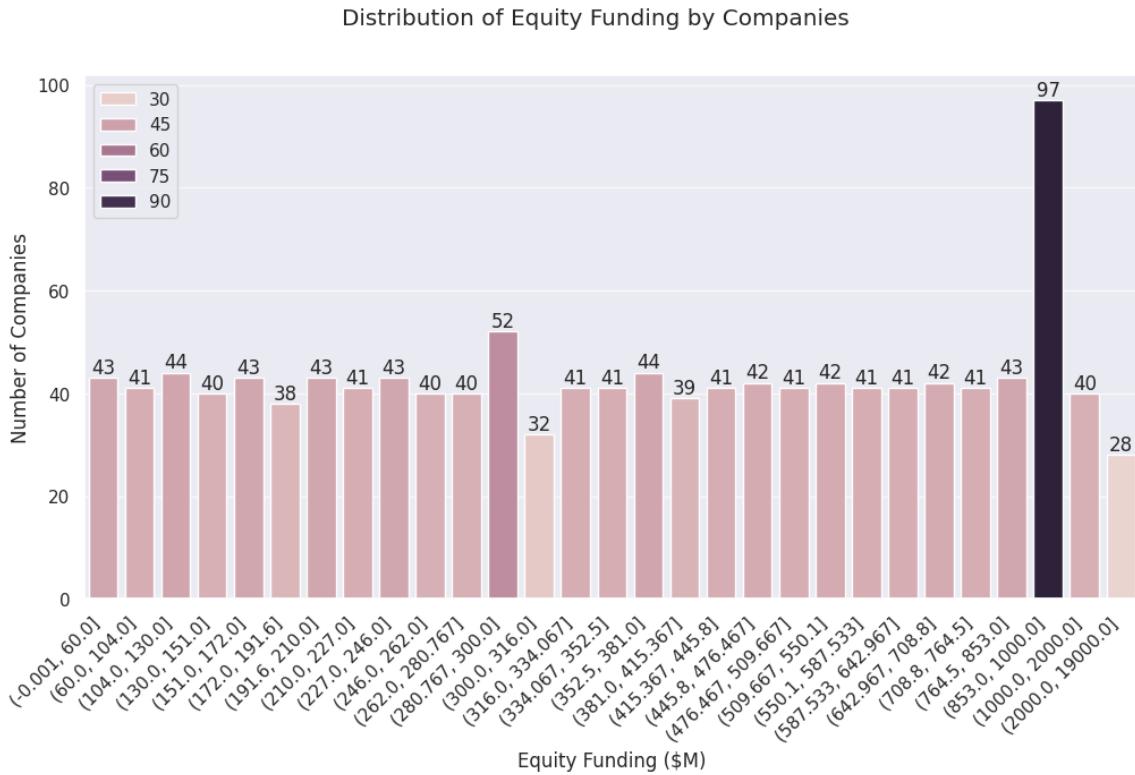
cuts = pd.qcut(df['Funding ($M)'], 30, duplicates='drop')

# Count the number of companies in each bin
distribution = cuts.value_counts().sort_index()

# Plot the Bar Chart
plt.figure(figsize=(12, 6))
ax = sns.barplot(x=distribution.index,
                  y=distribution.values, hue=distribution.values)
for i in ax.containers:
    ax.bar_label(i)
plt.suptitle('Distribution of Equity Funding by Companies')
plt.xlabel('Equity Funding ($M)')
plt.ylabel('Number of Companies')
plt.xticks(rotation=45, ha='right')

```

```
plt.grid(axis='y', alpha=0.75)
plt.show()
```



## 3.5 Investor Analysis

### 3.5.1 Top Investors

```
def top_investors_agg(grp):
    return pd.Series({'count': grp['Company'].size,
                      'valuation': grp['Latest Valuation ($B)'].sum(),
                      'companies': ', '.join(grp.nlargest(3, 'Latest Valuation
                                   ($B)')['Company'])})
top_investors = df.explode('Investors')\
    .groupby('Investors')[['Company', 'Latest Valuation ($B)']]\
    .apply(top_investors_agg)\n    .sort_values(by=['valuation', 'count'], ascending=False)\n    .head(50)
top_investors
```

Investors	count	valuation	companies
RRE Ventures	5	397.6	SpaceX, Fanatics, Gopuff
Founders Fund	24	363.01	OpenAI, Scale AI, Articulate
Relay Ventures	2	358	SpaceX, Flexport
Opus Capital	2	355.68	SpaceX, RELEX
Breyer Capital	5	320.16	ByteDance, Promasidor Holdings, Generate Bi
Parkway VC	2	316	ByteDance, EcoVadis
TIME Ventures	1	315	ByteDance
Susa Ventures	2	304.9	OpenAI, Meesho
Dynamo VC	1	300	OpenAI
Sequoia Capital China	40	183.61	Stripe, Miro, Airwallex
Andreessen Horowitz	71	179.01	Bitmain Technologies, Digital Currency Group
Sequoia Capital	59	176.7	Faire, Bitmain Technologies, Airtable
Alibaba Group	9	163.39	Ant Group, Starburst, Redis
Accel	65	161.91	DJI Innovations, Checkout.com, Dapper Labs
New Enterprise Associates	26	157.5	Anthropic, DJI Innovations, Celonis
The Carlyle Group	5	154.55	Ant Group, Paradox, InCred
CPP Investments	1	150	Ant Group
Tiger Global Management	56	144.47	Devoted Health, Ripple, OYO Rooms
General Atlantic	30	138.95	Databricks, Chime, Ro
Index Ventures	38	138.65	Canva, Scale AI, Airtable
Lightspeed Venture Partners	42	121.19	Nature's Fynd, Xiaohongshu, ServiceTitan
TDM Growth Partners	2	121	xAI, FalconX
Insight Partners	49	120.07	OpenSea, Airtable, Gusto
Baillie Gifford & Co.	3	117.4	xAI, Carbon, Clip
Prysm Capital	2	115.1	xAI, GoCardless
General Catalyst	41	113.46	Safe Superintelligence, Dapper Labs, Back Ma
ZhenFund	7	108.2	Stripe, Dream11, Physical Intelligence
K2 Ventures	1	91.5	Stripe
Institutional Venture Partners	13	85.24	Anthropic, ClickUp, Flock Safety
Temasek	10	74.58	Canva, Xingsheng Selected, Huolala
IDG Capital	27	72.08	Talkdesk, SumUp, Airwallex
Bessemer Venture Partners	32	70.31	OpenSea, ServiceTitan, Dataiku
Tencent Holdings	29	69.03	OYO Rooms, Bolt, Gemini
Google Ventures	28	68.81	Faire, Attentive, OakNorth Bank
369 Growth Partners	1	66	SHEIN
Berkeley Hills Capital	1	66	SHEIN
GTM Capital	1	66	SHEIN
Holtzbrinck Ventures	2	64	Databricks, Mysten Labs
Unternehmertum Venture Capital	1	62	Databricks
NVentures	1	61.5	Anthropic
Sequoia Capital India	23	57.97	Plaid, ContentSquare, Collibra
SoftBank Group	28	54.18	Trade Republic, Hopper, Impossible Foods
Coatue Management	21	53.79	Discord, Airwallex, Arctic Wolf Networks
Norwest Venture Partners	18	53.43	Anduril, Ripple, Houzz
Bain Capital Ventures	17	52.66	Kavak, Toss, Ziroom
Foresite Capital	4	49.2	CoreWeave, CoreWeave, Front
Thrive Capital	20	48.81	Netskope, Wiz, Checkr
CPV	17	48.18	Netskope, Gemini, Helpling

```

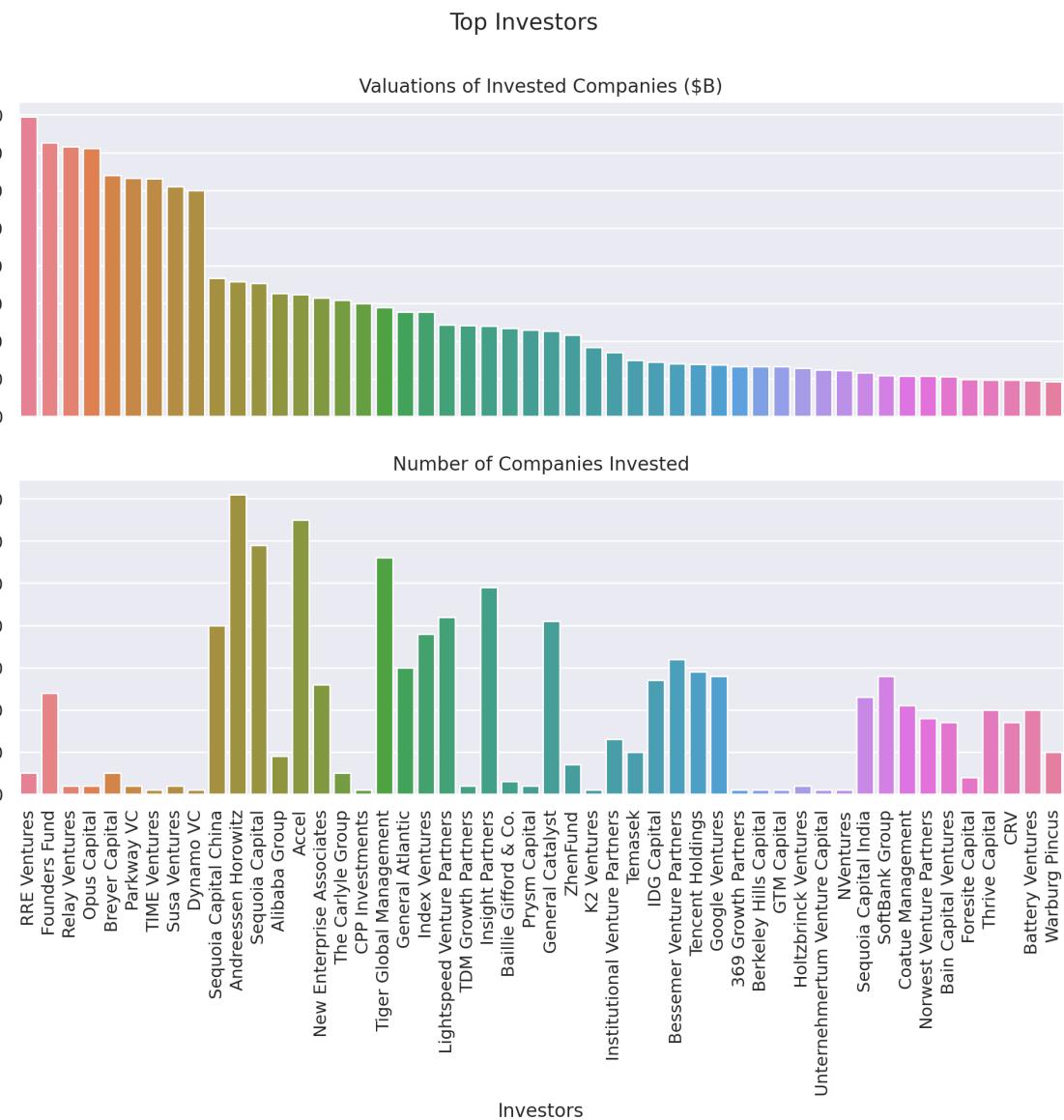
fig, ax = plt.subplots(2, 1, figsize=(12, 8), sharex=True)

sns.barplot(top_investors, ax=ax[0], y='valuation', x=top_investors.index,
            hue=top_investors.index, legend=False)
ax[0].set(ylabel=None, title='Valuations of Invested Companies ($B)')

sns.barplot(top_investors, ax=ax[1], y='count', x=top_investors.index,
            hue=top_investors.index, legend=False)
ax[1].set(ylabel=None, title='Number of Companies Invested')

plt.xticks(rotation=90)
plt.suptitle('Top Investors')
plt.show()

```



## 3.6 Founder Analysis

### 3.6.1 Top Founders

```
top_founders = df.explode('Founder(s)')\
    .groupby('Founder(s))')[['Latest Valuation ($B)', 'Company']]\
    .agg(count=('Company', 'count'), companies=('Company', lambda x: \
        x.join(x)), valuation=('Latest Valuation ($B)', 'sum'))\
    .sort_values(by=['valuation', 'count'], ascending=False)\n    .head(50)
print(top_founders)
```

Founder(s)	count	companies	valuation
Elon Musk	3	SpaceX, xAI, The Boring Company	468.70
Ilya Sutskever	2	OpenAI, Safe Superintelligence	332.00
Liang Rubo	1	ByteDance	315.00
Zhang Yiming	1	ByteDance	315.00
Greg Brockman	1	OpenAI	300.00
Sam Altman	1	OpenAI	300.00
John Collison	1	Stripe	91.50
Patrick	1	Stripe	91.50
Chris Xu	1	SHEIN	66.00
Ali Ghodsi	1	Databricks	62.00
Dario Amodei	1	Anthropic	61.50
Cameron Adams	1	Canva	32.00
Clifford Obrecht	1	Canva	32.00
Daniel Gross	1	Safe Superintelligence	32.00
Daniel Levy	1	Safe Superintelligence	32.00
Melanie Perkins	1	Canva	32.00
Tim Sweeney	1	Epic Games	31.50
Alexandr Wang	1	Scale AI	29.00
Lucy Guo	1	Scale AI	29.00
Alan Trager	1	Fanatics	27.00
Michael Rubin[34]	1	Fanatics	27.00
Mitch Trager	1	Fanatics	27.00
Chris Britt	1	Chime	25.00
Ryan King	1	Chime	25.00
Nikolay Storonsky	1	Revolut	17.75
Vlad Yatsenko	1	Revolut	17.75
Andrey Khusid	1	Miro	17.50
Daniel Livny	1	Nature's Fynd	17.00
Mark Kozubal	1	Nature's Fynd	17.00
Matthew Strongin	1	Nature's Fynd	17.00
Rich Macur	1	Nature's Fynd	17.00

Thomas Jonas	1	Nature's Fynd	17.00
Yuval Avniel	1	Nature's Fynd	17.00
Markus Villig	2	Bolt, Bolt	16.80
Yong Li	1	Yuanfudao	15.50
Jason Citron	1	Discord	15.00
Rafael Ilishayev	1	Gopuff	15.00
Stanislav Vishnevsky	1	Discord	15.00
Yakir Gola	1	Gopuff	15.00
Charlwin Mao Wenchao	1	Xiaohongshu	14.00
Miranda Qu Fang	1	Xiaohongshu	14.00
William Hockey	1	Plaid	13.40
Zach Perret	1	Plaid	13.40
Alex Shevchenko	1	Grammarly	13.00
Dmytro Lider	1	Grammarly	13.00
Max Lytvyn,	1	Grammarly	13.00
Todd Park	1	Devoted Health	12.60
Max Rhodes	1	Faire	12.40
Henrique Dubugras	1	Brex	12.30
Pedro Franceschi	1	Brex	12.30

---

```

fig, ax = plt.subplots(figsize=(12, 8), dpi=300, sharex=True)

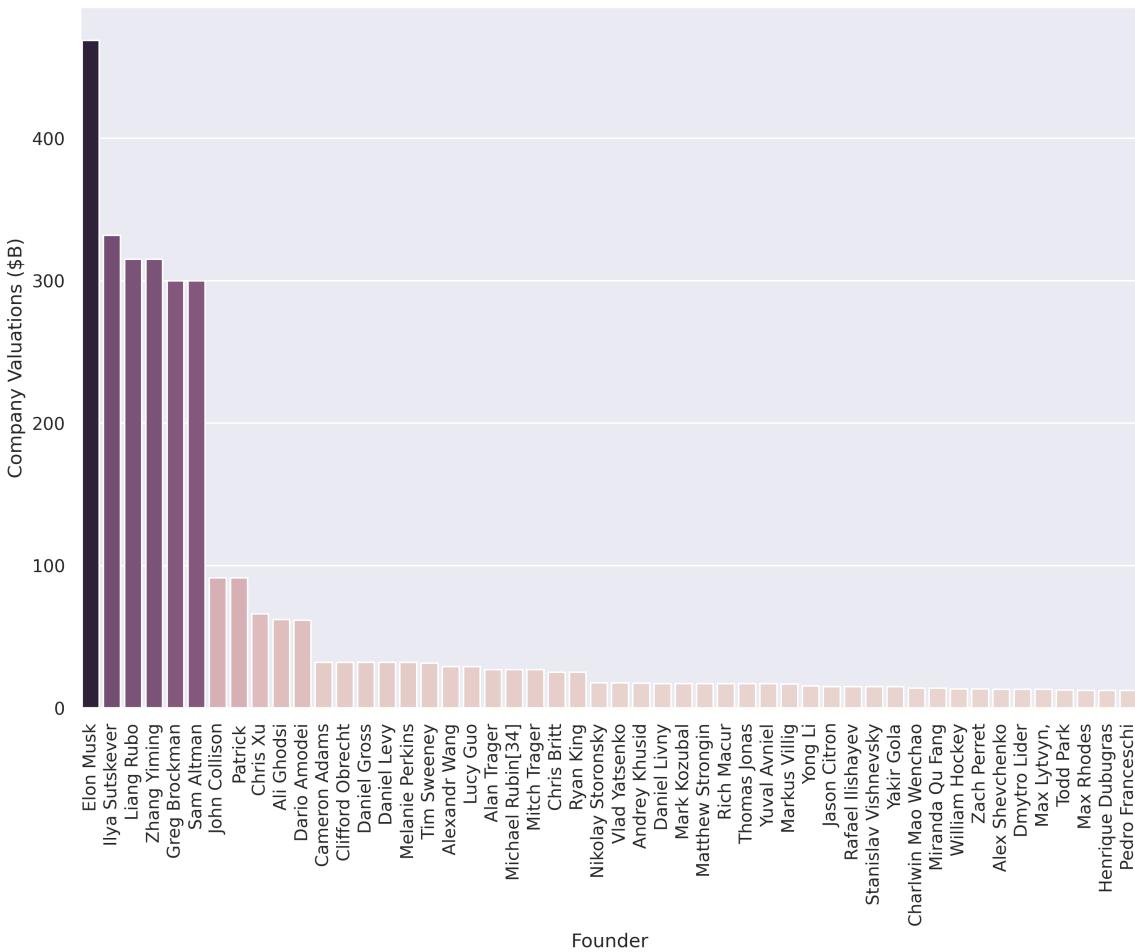
ax = sns.barplot(top_founders, y='valuation', x=top_founders.index, hue='valuation',
                  legend=False)
ax.set(ylabel='Company Valuations ($B)', xlabel='Founder')

plt.xticks(rotation=90)
plt.suptitle('Top Founders by Company Valuations')
plt.show()

```

---

Top Founders by Company Valuations



## 4 Time-Based Analysis

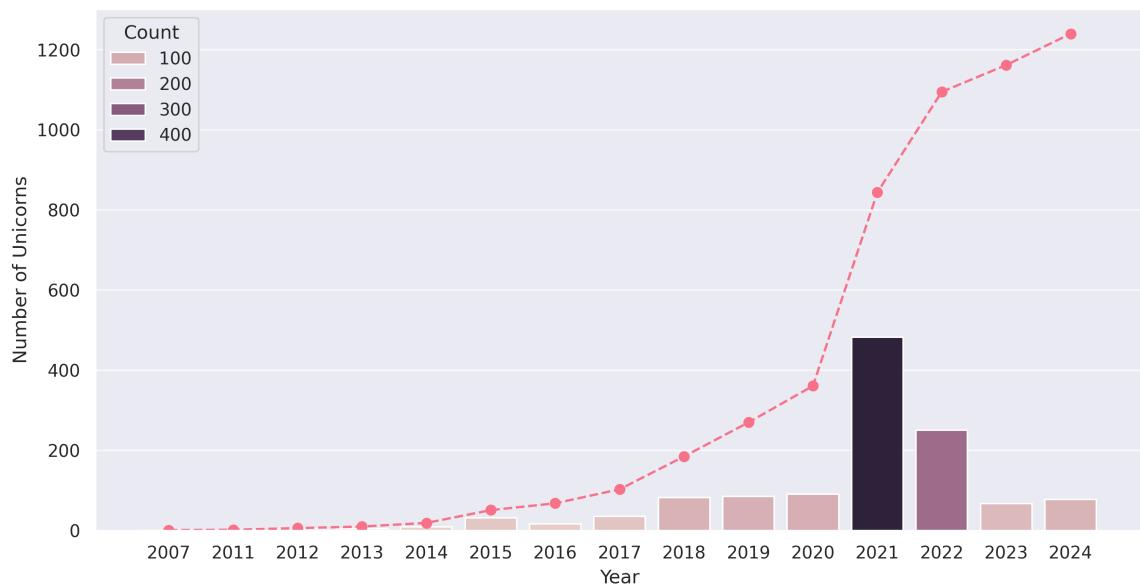
### 4.1 Unicorn Growth Over Time

```
_df = df.groupby('Unicorn Year').size().reset_index(name='Count')
_df['Accumulated Count'] = _df['Count'].cumsum()
_df
```

```
plt.subplots(figsize=(12, 6), dpi=300)
sns.barplot(_df, x='Unicorn Year', y='Count', hue='Count')
plt.plot(_df['Accumulated Count'], marker='o', linestyle='dashed')
plt.suptitle('Unicorn Growth Over Time')
plt.xlabel('Year')
plt.ylabel('Number of Unicorns')
plt.grid(axis='y', alpha=0.7)
plt.show()
```

	Unicorn Year	Count	Accumulated Count
0	2007	1	1
1	2011	1	2
2	2012	4	6
3	2013	4	10
4	2014	9	19
5	2015	32	51
6	2016	17	68
7	2017	35	103
8	2018	82	185
9	2019	85	270
10	2020	91	361
11	2021	483	844
12	2022	251	1095
13	2023	67	1162
14	2024	78	1240

Unicorn Growth Over Time



The surge of unicorns was reported as “[meteoric](#)” for 2021, with \$71 billion invested in 340 new companies, a banner year for startups and for the US venture capital industry; the unprecedented number of companies valued at more than \$1 billion during 2021 exceeded the sum total of the five previous years.

## 4.2 Time to Unicorn

---

```
# Calculate 5th and 95th percentiles
lower_bound = df['Years to Unicorn'].quantile(0.05)
upper_bound = df['Years to Unicorn'].quantile(0.95)
```

```

# Filter out values outside the 5th and 95th percentiles
df_filtered = df[(df['Years to Unicorn'] >= lower_bound) & (df['Years to Unicorn'] <=
→ upper_bound)]

fig, ax = plt.subplots(2, 1, figsize=(12, 8))
sns.boxplot(df_filtered, x='Years to Unicorn', y='Industry', hue='Industry', ax=ax[0],
→ showfliers=False)
ax[0].set(xlabel=None)
sns.histplot(df_filtered['Years to Unicorn'].dropna(), bins=50, ax=ax[1], kde=True)
ax[1].set(xlabel='Years', ylabel='Number of Companies')
plt.suptitle('Distribution of Time to Unicorn')
plt.grid(alpha=0.75)
plt.show()

```

---



## 4.3 Distribution of Valuations Over Time

---

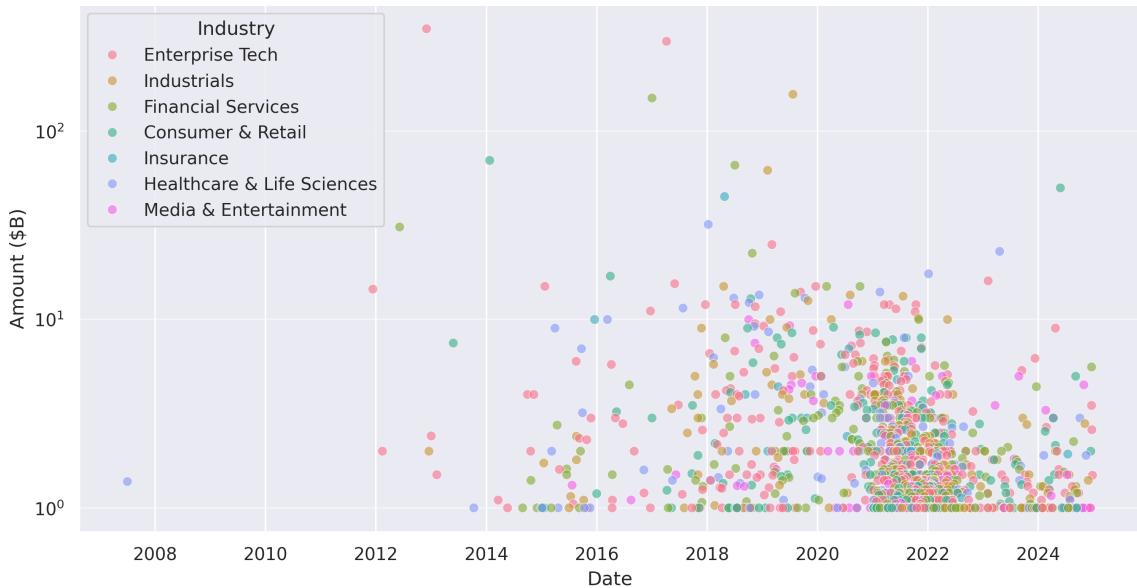
```

plt.subplots(figsize=(12, 6), dpi=300)
sns.scatterplot(df, x='Unicorn Date', y='Valuation ($B)', alpha=.6, hue='Industry')
plt.suptitle('Distribution of Valuations Over Time')
plt.xlabel('Date')
plt.ylabel('Amount ($B)')
# plt.xticks(df['Unicorn Year'].unique(), rotation=45)
plt.grid(axis='y', alpha=0.5)
plt.yscale('log')
plt.show()

```

---

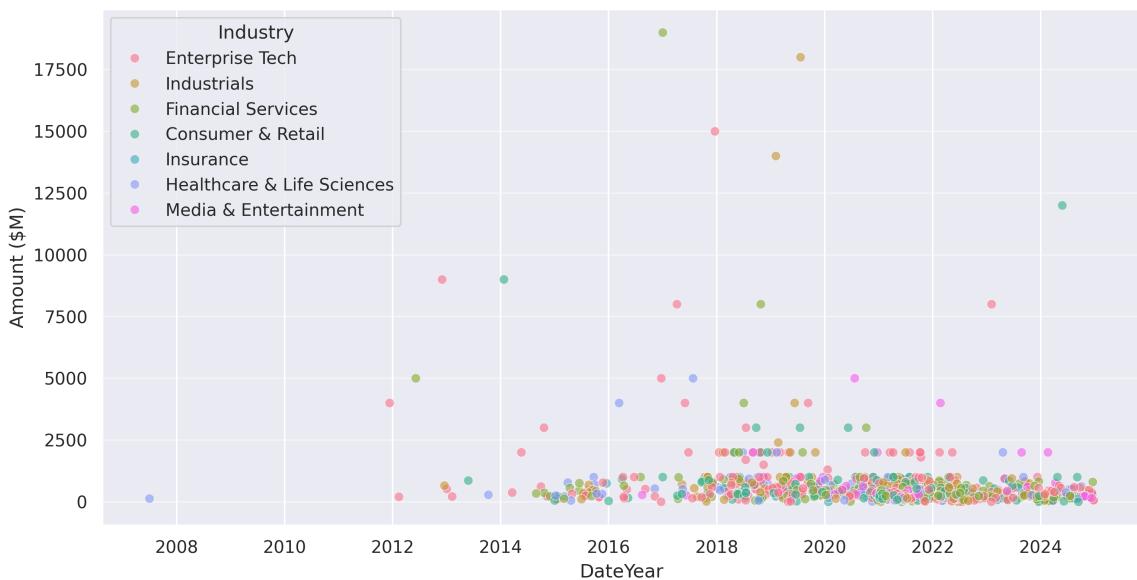
Distribution of Valuations Over Time



## 4.4 Distribution of Funding Over Time

```
plt.subplots(figsize=(12, 6), dpi=300)
sns.scatterplot(df, x='Unicorn Date', y=df['Funding ($M)'], alpha=0.6, hue='Industry')
plt.suptitle('Distribution of Funding Over Time')
plt.xlabel('Date')
plt.ylabel('Amount ($M)')
# plt.xticks(df['Unicorn Year'].unique(), rotation=45)
plt.grid(axis='y', alpha=0.5)
# plt.yscale('log')
plt.show()
```

Distribution of Funding Over Time

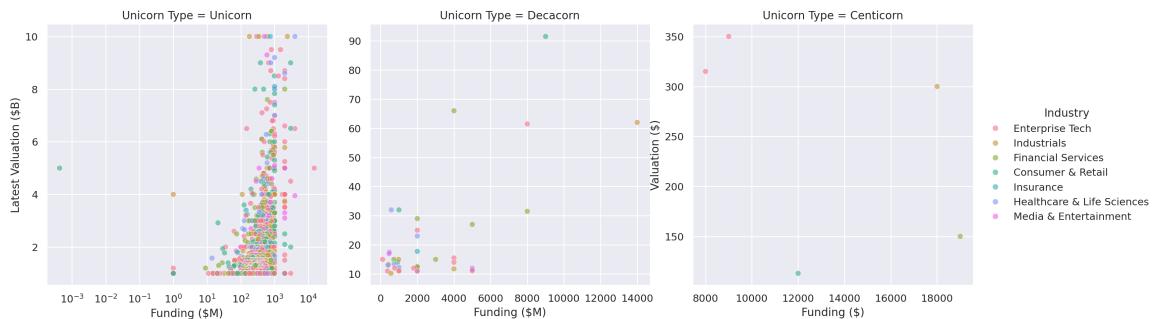


# 5 Correlation Analysis

## 5.1 Relationship between Funding and Valuation

```
df_filtered = df[(df['Total Equity Funding ($)'] >= df['Total Equity Funding ($)' .quantile(0.05)) &
                   (df['Total Equity Funding ($)'] <= df['Total Equity Funding ($)' .quantile(0.95)) &
                   (df['Valuation ($)'] >= df['Valuation ($)'].quantile(0.05)) &
                   (df['Valuation ($)'] <= df['Valuation ($)'].quantile(0.95))]

# plt.subplots(figsize=(12, 8), dpi=300)
# sns.relplot(df, x='Total Equity Funding ($)', y='Valuation ($)', alpha=0.6,
#             hue='Industry', row='Unicorn Type')
# print(df[df['Unicorn Type']=='Centic平'][['Valuation ($B)', 'Funding ($B)']].corr())
g = sns.relplot(df, x='Funding ($M)', y='Latest Valuation ($B)',
                 alpha=0.6, hue='Industry', col='Unicorn Type',
                 facet_kws={'sharey':False, 'sharex':False})
g.axes[0,0].set(xscale='log')
# sns.jointplot(df_filtered, x='Total Equity Funding ($)', y='Valuation ($)', kind='reg',
#                truncate=False, height=7)
# plt.suptitle('Relationship between Funding and Valuation')
plt.xlabel('Funding ($)')
plt.ylabel('Valuation ($)')
plt.grid(True)
# plt.xscale('log')
# plt.yscale('log')
plt.show()
```



## 5.2 Relationship between Time to Unicorn and Valuation

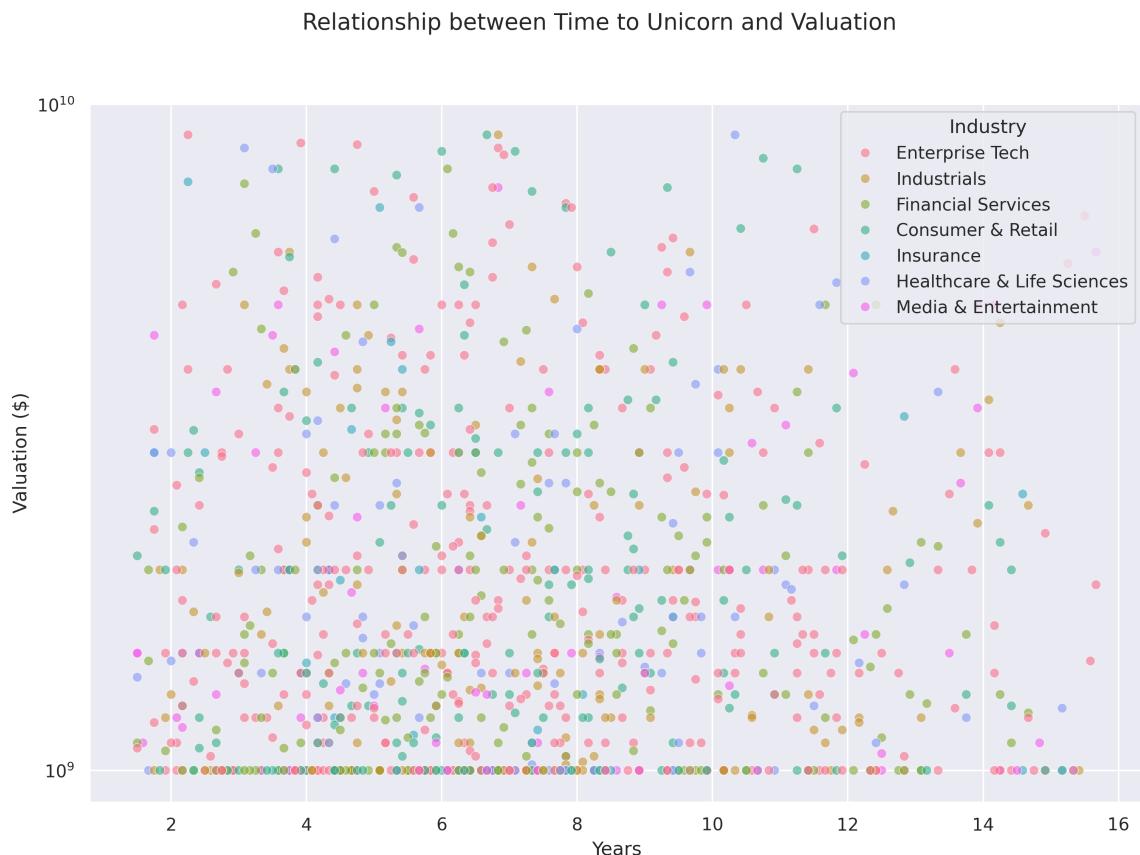
```
# Filter out values outside the 5th and 95th percentiles
df_filtered = df[(df['Years to Unicorn'] >= df['Years to Unicorn'].quantile(0.05)) &
                  (df['Years to Unicorn'] <= df['Years to Unicorn'].quantile(0.95)) &
                  (df['Valuation ($)'] >= df['Valuation ($)'].quantile(0.05)) &
                  (df['Valuation ($)'] <= df['Valuation ($)'].quantile(0.95))]

plt.subplots(figsize=(12, 8), dpi=300)
sns.scatterplot(df, x=df_filtered['Years to Unicorn'], y=df['Valuation ($)'), alpha=0.6,
                hue='Industry')
```

```

plt.suptitle('Relationship between Time to Unicorn and Valuation')
plt.xlabel('Years')
plt.ylabel('Valuation ($)')
plt.grid(True)
plt.yscale('log')
plt.show()

```



## 6 Historical Analysis

### 6.1 Survival and Acquisition

- Find out companies no longer listed as unicorns in 2024

```

df_2022 = pd.read_csv('input/datasets/Unicorn_Companies (March 2022).csv')
df_2022['Valuation ($B)'] = pd.to_numeric(df_2022['Valuation ($B)'].str.replace('$',
                           ''))

df_exit = df_2022[~df_2022['Company'].str.lower().isin(df['Company'].str.lower())]

```

178 companies no longer listed in 2024 unicorn list

```
print(df_exit.head())
```

	Company	Valuation (\$B)	Date Joined	Country	Cit
7	Instacart	39.00	12/30/2014	United States	San Francisco
10	FTX	32.00	7/20/2021	Bahamas	Fintech
15	J&T Express	20.00	4/7/2021	Indonesia	Jakarta
31	Biosplice Therapeutics	12.00	8/6/2018	United States	San Diego
39	Weilong	10.88	5/8/2021	China	Luohe
	Total Raised Financial Stage	Investors Count	Deal Terms	Portfolio	Exits
7	\$2.686B	NaN	29.0	12.0	NaN
10	\$1.829B	Acq	40.0	3.0	1.0
15	\$4.653B	NaN	9.0	3.0	NaN
31	\$561.5M	NaN	10.0	1.0	NaN
39	\$559.74M	NaN	7.0	1.0	NaN

- Financial Stage

---

```
df_2022['Financial Stage'].value_counts()
```

---

#### Financial Stage

Acquired	22
Divestiture	8
IPO	7
Acq	7
Asset	1
Take	1
Management	1
Reverse	1
Corporate	1

Name: count, dtype: int64

### 6.1.1 Top Exited Unicorns as of March 2022

---

```
df_exit_top_companies = df_exit.sort_values('Valuation ($B)', ascending=False).head(20)
# print(df_exit_top_companies)
```

---



---

```
plt.subplots(figsize=(12, 6), dpi=300)
ax = sns.barplot(df_exit_top_companies,
                  x='Company',
                  y='Valuation ($B)',
                  hue='Company')
for i in ax.containers:
    ax.bar_label(i)
plt.suptitle('Top Exited Unicorns as of March 2022')
```

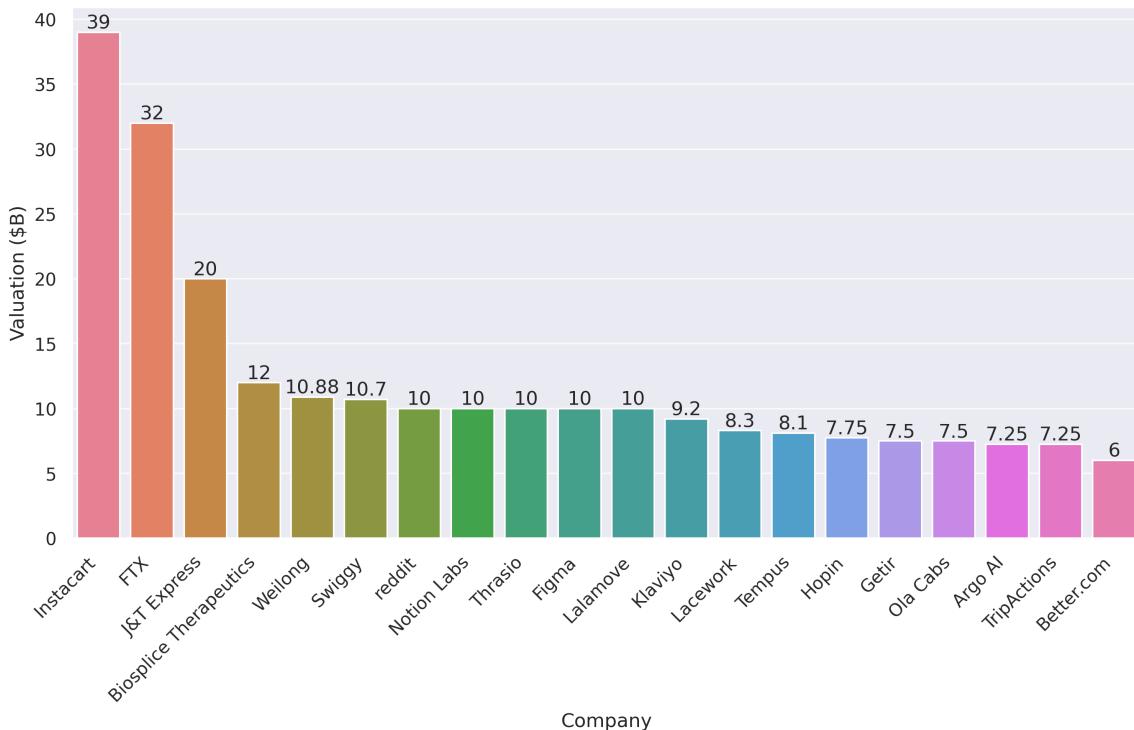
---

```

plt.ylabel('Valuation ($B)')
plt.xlabel('Company')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', alpha=0.75)
plt.show()

```

Top Exited Unicorns as of March 2022



### Insights:

- **Leading Exited Unicorn:**

**Instacart** stands out as the top exited unicorn with a valuation of **\$39B**. This indicates significant market presence and investor confidence prior to its exit.

- **Notable Competitors:**

- **FTX**, despite its subsequent bankruptcy, had a valuation of **\$32B**, highlighting its rapid growth and substantial funding within the cryptocurrency sector.
- **J&T Express** and **Biosplice Therapeutics** follow with valuations of **\$20B** and **\$12B**, respectively, indicating strong competition in logistics and healthcare sectors.

- **Diverse Industries:**

- The chart features unicorns across various industries, including logistics (J&T Express), biotechnology (Biosplice Therapeutics), food delivery (Swiggy), and technology (NerdWallet, Robinhood).

- This diversity underscores the broad appeal and investment potential across different sectors.

- **Valuation Range:**

The valuations of exited unicorns vary significantly, with the lowest being \$6B (related to Beekeeper). This range suggests that while some companies achieved massive scale, others still represented substantial exits.

- **Market Trends:**

The presence of companies like **Swiggy** and **NerdWallet** indicates ongoing investor interest in technology-driven solutions, particularly in food delivery and financial services.

- **Implications for Investors:**

- The valuations reflect both the potential for high returns in emerging sectors and the risks associated with exits, as demonstrated by FTX's downfall.
- Investors may consider industry trends and market demands when evaluating future investments in unicorns.

### 6.1.2 Exit Reasons of Former Unicorns

---

```
_df = pd.read_csv('input/raw_data/list-of-unicorn-former-startups_20250619
                   (wikipedia).csv')
_df['Company'] = _df['Company'].str.strip()
def correct_exit_reasons(s):
    s = re.sub(r'\[.*\]', '', s)
    s= s.strip()
    if 'merge' in s.lower():
        return 'Merged'
    if 'acquire' in s.lower() or 'acquisition' in s.lower() or 'takeover' in s.lower():
        return 'Acquired'
    if 'devaluation' == s.lower():
        return 'Devalued'
    if 'direct listing' == s.lower():
        return 'IPO'
    return s
_df['Exit reason'] = _df['Exit reason'].dropna().apply(correct_exit_reasons)
# _df = _df[_df['Company'].str.lower().isin(df_exit['Company'].str.lower())]
_df['Exit reason'].value_counts()
```

---

#### Exit reason

IPO	128
Acquired	53
Merged	14
Defunct	3

```

Devalued      3
Bankruptcy    2
Name: count, dtype: int64

```

---

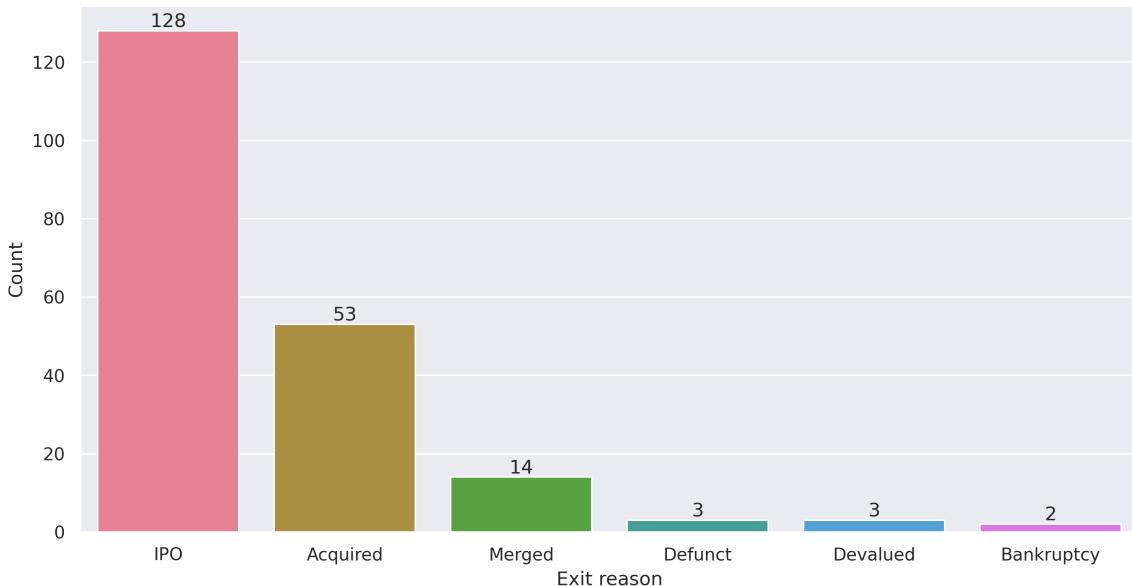
```

exit_reasons = _df['Exit reason'].value_counts().reset_index(name='Count')
# print(exit_reasons.index)
plt.subplots(figsize=(12, 6), dpi=300)
ax = sns.barplot(exit_reasons, x='Exit reason', y='Count', hue='Exit reason')
for i in ax.containers:
    ax.bar_label(i)
plt.suptitle('Exit Reasons of Former Unicorns')
plt.show()

```

---

Exit Reasons of Former Unicorns



The chart illustrates that most unicorns have successful exit strategies, predominantly through IPOs and acquisitions. The relatively low numbers for defunct, devalued, and bankrupt companies indicate that, despite challenges, the unicorn landscape has robust potential for growth and successful exits. This information is valuable for investors assessing the viability and longevity of unicorn businesses.

## 7 Funded by Y-Combinator

Y Combinator, founded in 2005 by Paul Graham and others, is a prestigious startup accelerator based in Silicon Valley that provides early-stage companies with seed funding, mentorship, and resources over a three-month program held twice a year. Startups receive initial funding in exchange for equity and culminate in a Demo Day where they pitch to investors. Y Combinator has launched successful companies like Airbnb, Dropbox, and Stripe, significantly impacting the startup ecosystem and inspiring numerous other accelerators globally.

- Datasets

- YC Companies

```
df_yc_companies = pd.read_csv('input/datasets/2024 YCombinator All Companies
                                → Dataset/companies.csv')

df_yc_industries = pd.read_csv('input/datasets/2024 YCombinator All Companies
                                → Dataset/industries.csv')
df_yc_tags = pd.read_csv('input/datasets/2024 YCombinator All Companies
                                → Dataset/tags.csv')
# print(df_yc_tags.groupby('id')['tag'].agg(list).reset_index())
df_yc_companies = df_yc_companies.merge(df_yc_industries[['id',
                                → 'industry']].groupby('id')['industry'].agg(list).reset_index(), on='id',
                                → how='left')
df_yc_companies =
    → df_yc_companies.merge(df_yc_tags.groupby('id')['tag'].agg(list).reset_index(),
                                → on='id', how='left')
df_yc_companies = df_yc_companies[['name', 'slug', 'oneLiner', 'website',
                                → 'smallLogoUrl', 'teamSize', 'tag', 'industry', 'batch']].rename(columns={
        'name': 'Company',
        'slug': 'Slug',
        'oneLiner': 'Short Description',
        'website': 'Website',
        'smallLogoUrl': 'Logo',
        'teamSize': 'Team Size',
        'tag': 'Tags',
        'industry': 'Industries',
        'batch': 'Batch'
})
print(df_yc_companies.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4844 entries, 0 to 4843
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   Company          4844 non-null   object 
 1   Slug              4841 non-null   object 
 2   Short Description 4692 non-null   object 
 3   Website           4817 non-null   object 
 4   Logo               4197 non-null   object 
 5   Team Size          4766 non-null   float64
 6   Tags               4463 non-null   object 
 7   Industries         4825 non-null   object 
 8   Batch              4844 non-null   object 
dtypes: float64(1), object(8)
memory usage: 340.7+ KB
None
```

```
df2_yc_companies = pd.read_json('input/datasets/yc_startups.json')
print(df2_yc_companies.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 12 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   name            1000 non-null    object  
 1   description     1000 non-null    object  
 2   location         1000 non-null    object  
 3   url              1000 non-null    object  
 4   tags              1000 non-null    object  
 5   site_url         999 non-null    object  
 6   tag_line          999 non-null    object  
 7   long_desc         999 non-null    object  
 8   thumbnail         975 non-null    object  
 9   founders          999 non-null    object  
 10  meta              999 non-null    object  
 11  socials           999 non-null    object  
dtypes: object(12)
memory usage: 93.9+ KB
None
```

## ▪ YC Founders

```
df_yc_founders = pd.read_csv('input/datasets/2024 YCombinator All Companies
→ Dataset/founders.csv')
print(df_yc_founders.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8465 entries, 0 to 8464
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype  
---  --  
 0   first_name       8461 non-null    object  
 1   last_name        8456 non-null    object  
 2   hnid             8465 non-null    object  
 3   avatar_thumb     8465 non-null    object  
 4   current_company  7624 non-null    object  
 5   current_title    2201 non-null    object  
 6   company_slug     8465 non-null    object  
 7   top_company      8465 non-null    bool  
dtypes: bool(1), object(7)
```

```
memory usage: 471.3+ KB
```

```
None
```

## 7.1 How many YC companies are in unicorn status currently?

---

```
df_yc_unicorns = df.assign(tmp_col=df.Company.str.lower()).merge(
    df_yc_companies[['Company', 'Slug', 'Short Description', 'Website', 'Logo', 'Team
    → Size', 'Tags', 'Industries', 'Batch']].assign(tmp_col=lambda x:
    → x.Company.str.lower()),
    on='tmp_col', how='inner').drop(['tmp_col', 'Company_y'],
    → axis=1).rename(columns={'Company_x': 'Company'})
df_yc_unicorns['Batch Season'] = df_yc_unicorns['Batch'].apply(lambda x: 'Summer' if
    → x[0]=='S' else 'Winter')
df_yc_unicorns['Batch Year'] = pd.to_numeric(df_yc_unicorns['Batch'].apply(lambda x:
    → f'20{x[1:]}'))
print(df_yc_unicorns.info())
```

---

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 98 entries, 0 to 97
Data columns (total 29 columns):
 #   Column           Non-Null Count  Dtype  
---  -- 
 0   Company          98 non-null     object 
 1   Valuation ($B)   98 non-null     float64
 2   Total Equity Funding ($) 98 non-null     int64  
 3   Unicorn Date    98 non-null     datetime64[ns]
 4   Date Founded    98 non-null     int64  
 5   Years to Unicorn 98 non-null     object 
 6   Industry         98 non-null     object 
 7   Country          98 non-null     object 
 8   City              98 non-null     object 
 9   Select Investors 98 non-null     object 
 10  Valuation ($)    98 non-null     float64
 11  Unicorn Year    98 non-null     int32  
 12  Funding ($B)    98 non-null     float64
 13  Funding ($M)    98 non-null     float64
 14  Investors        98 non-null     object 
 15  Years to Unicorn (Months) 98 non-null     int64  
 16  Years to Unicorn (Converted) 98 non-null     float64
 17  Latest Valuation ($B) 98 non-null     float64
 18  Founder(s)      16 non-null     object 
 19  Slug             98 non-null     object 
 20  Short Description 97 non-null     object 
 21  Website          98 non-null     object 
```

```

22 Logo                      95 non-null      object
23 Team Size                 96 non-null      float64
24 Tags                      92 non-null      object
25 Industries                98 non-null      object
26 Batch                     98 non-null      object
27 Batch Season              98 non-null      object
28 Batch Year                98 non-null      int64
dtypes: datetime64[ns](1), float64(7), int32(1), int64(4), object(16)
memory usage: 21.9+ KB
None

```

## 7.2 Top Companies by Valuation

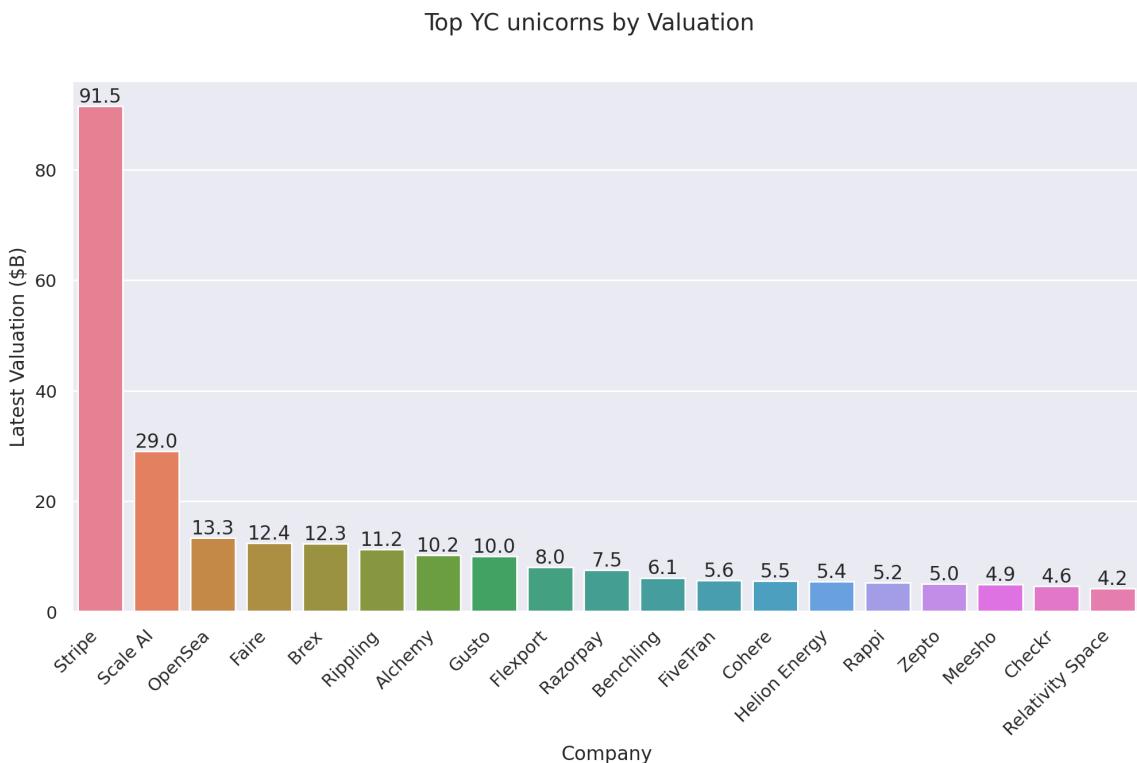
---

```

df_top_yc_unicorns = df_yc_unicorns.sort_values(by='Latest Valuation ($B)',
→ ascending=False).head(20)
fig, ax = plt.subplots(figsize=(12,6), dpi=200)
ax = sns.barplot(data=df_top_yc_unicorns, x='Company', y='Latest Valuation ($B)',
→ hue='Company')
for i in ax.containers:
    ax.bar_label(i, fmt='%.1f')
plt.xticks(rotation=45, ha='right')
plt.suptitle('Top YC unicorns by Valuation')
plt.show()

```

---



The chart illustrates the valuation landscape of top Y Combinator unicorns, with Stripe leading substantially. The varied valuations reflect a healthy startup ecosystem with strong

growth potential across different sectors. Investors may find valuable opportunities by analyzing the performance and sectors of these unicorns.

## Insights:

- **Leading Unicorn:**

**Stripe** is the top unicorn with a valuation of **\$91.5B**, indicating its dominant position in the payment processing industry. This high valuation reflects the company's significant market impact and widespread adoption among businesses.

- **Strong Competitors:**

- **Scale AI** follows with a valuation of **\$29B**, showcasing its importance in the artificial intelligence sector. This positions Scale AI as a key player in the rapidly growing AI market.
- Other notable unicorns include **OpenSea** (\$13.3B) and **Brew** (Brewdog) (\$12.4B), highlighting the diversity of successful companies in sectors like blockchain and beverage.

- **Valuation Distribution:**

- The chart displays a significant drop in valuation from Stripe to Scale AI, indicating a steep decline in market leader dominance. The next highest valuations cluster around the \$10B mark, with several companies like Rippling, Alchemy, and Gusto valued between \$11B and \$13B.

- **Emerging Sectors:**

- Companies like **Flexport** and **Benchling** indicate strong interest in logistics and life sciences, respectively. This suggests that investors are keen on sectors with potential for innovation and growth.

- **Valuation Range:**

The lowest valuation among the listed unicorns is \$4.2B (Relativity Space), showing that while there is a significant range in valuations, all listed companies have achieved substantial market value as unicorns.

- **Investment Trends:**

The diversity among the top unicorns, covering industries from fintech to logistics and AI, suggests that venture capitalists are actively investing across various sectors. This diversification can mitigate risks associated with market fluctuations.

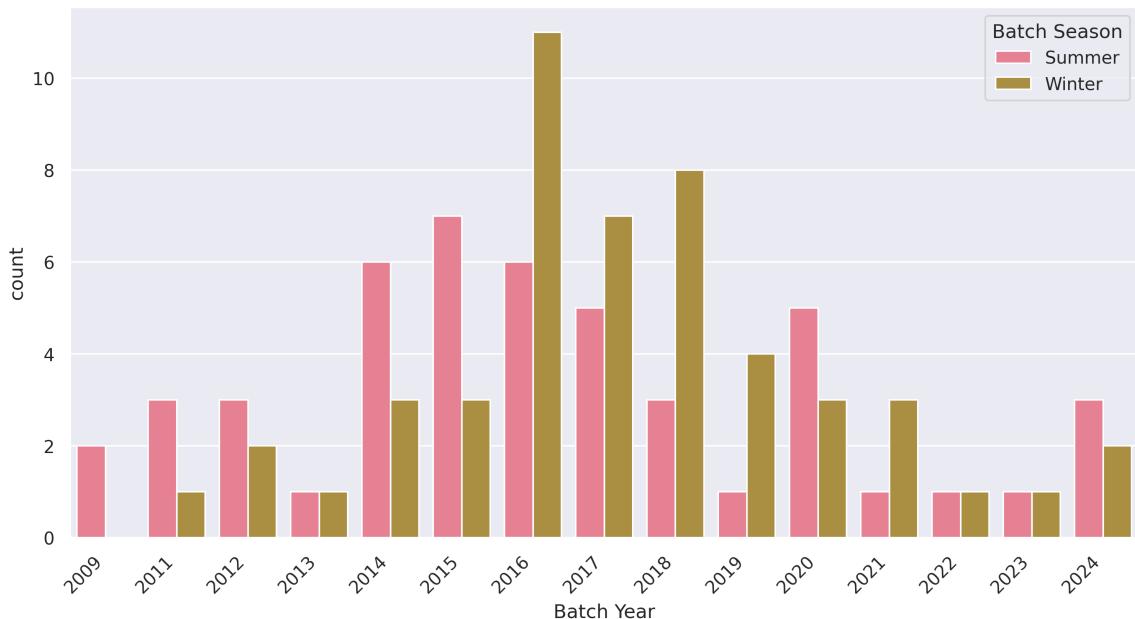
### 7.3 YC Batch Distribution

```
_df = df_yc_unicorns.groupby(['Batch Year', 'Batch  
→ Season']).size().reset_index(name='count').sort_values(by='Batch Year')  
print(_df)
```

	Batch Year	Batch Season	count
0	2009	Summer	2
1	2011	Summer	3
2	2011	Winter	1
3	2012	Summer	3
4	2012	Winter	2
5	2013	Summer	1
6	2013	Winter	1
7	2014	Summer	6
8	2014	Winter	3
9	2015	Summer	7
10	2015	Winter	3
11	2016	Summer	6
12	2016	Winter	11
14	2017	Winter	7
13	2017	Summer	5
15	2018	Summer	3
16	2018	Winter	8
17	2019	Summer	1
18	2019	Winter	4
19	2020	Summer	5
20	2020	Winter	3
21	2021	Summer	1
22	2021	Winter	3
23	2022	Summer	1
24	2022	Winter	1
25	2023	Summer	1
26	2023	Winter	1
27	2024	Summer	3
28	2024	Winter	2

```
plt.subplots(figsize=(12,6),dpi=300)  
sns.barplot(_df, x='Batch Year', y='count', hue='Batch Season')  
plt.xticks(rotation=45, ha='right')  
plt.suptitle('Batch Distribution of YC Unicorns')  
plt.show()
```

## Batch Distribution of YC Unicorns



## 7.4 Top Countries

```
top_countries = df_yc_unicorns['Country'].value_counts().nlargest(20).index
```

## 7.5 Top Categories

```
top_categories =  
    df_yc_unicorns['Tags'].explode().value_counts().head(20).reset_index(name='Count')  
print(top_categories)
```

	Tags	Count
0	SaaS	25
1	Fintech	22
2	B2B	17
3	Developer Tools	10
4	Artificial Intelligence	9
5	Machine Learning	7
6	Marketplace	7
7	HR Tech	6
8	E-commerce	5
9	AI	5

10	Payments	4
11	Logistics	4
12	Climate	4
13	Analytics	4
14	Enterprise	4
15	Automation	3
16	Data Engineering	3
17	Generative AI	3
18	Manufacturing	3
19	Education	3

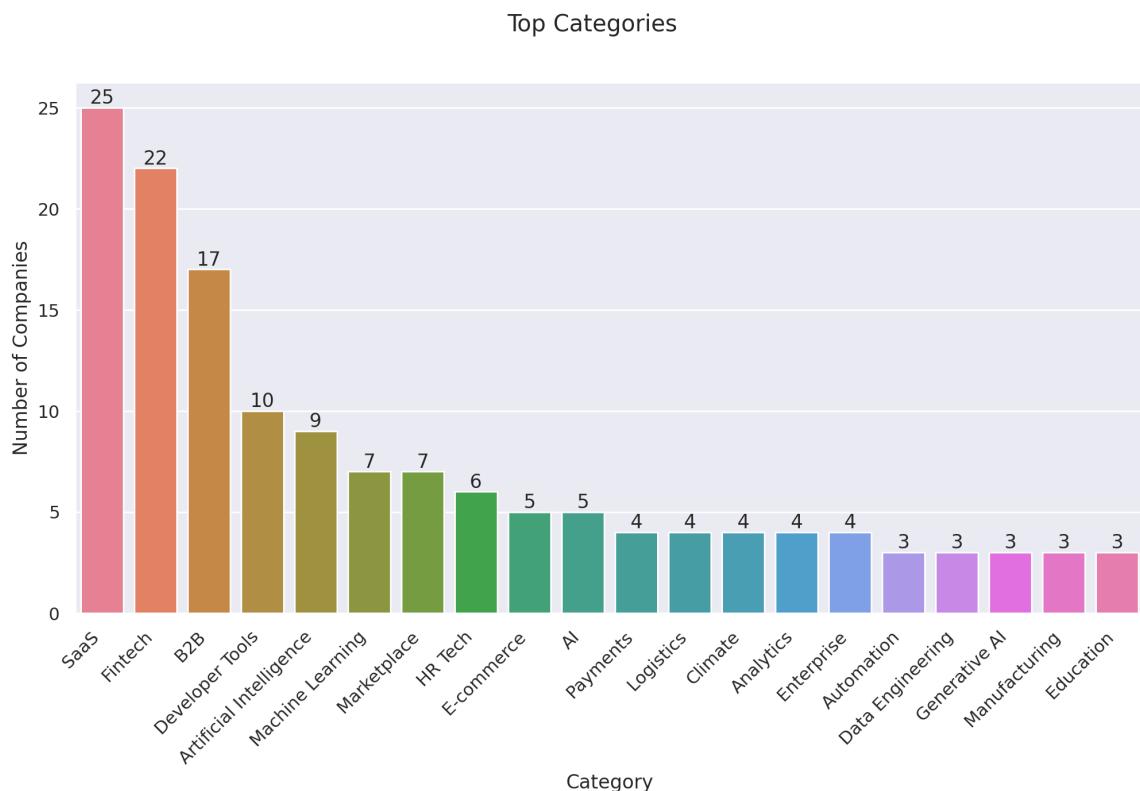
---

```

plt.subplots(figsize=(12,6), dpi=200)
ax = sns.barplot(data=top_categories, x='Tags', y='Count', hue='Tags')
ax.set(ylabel='Number of Companies',
       xlabel='Category')
for i in ax.containers:
    ax.bar_label(i)
plt.xticks(rotation=45, ha='right')
plt.suptitle('Top Categories')
plt.show()

```

---



## Insights:

- Dominant Category - SaaS:

**SaaS (Software as a Service)** leads the chart with **25 companies**, indicating a strong market demand for subscription-based software solutions. This category's popularity reflects the growing trend of businesses adopting cloud-based services.

- **Financial Technology (Fintech):**

**Fintech** follows closely with **22 companies**, showcasing the robust growth in financial services technology. The rise of digital payment solutions and financial management tools has driven significant interest in this sector.

- **Diverse Categories:**

Other notable categories include **Developer Tools** (17 companies) and **B2B** (10 companies), indicating a healthy ecosystem for tools that facilitate business operations and development.

- **Emerging Technologies:**

Categories such as **Artificial Intelligence** (9 companies) and **Machine Learning** (7 companies) illustrate the increasing focus on AI-driven solutions across various industries, reflecting investment trends in cutting-edge technology.

- **E-Commerce and HR Tech:**

**E-Commerce** and **HR Tech** both have 6 companies, indicating ongoing innovation and competition in online retail and human resources technology, respectively.

- **Other Notable Categories:**

Categories like **Payments**, **Logistics**, and **Clinical** have 4 companies each, highlighting niche markets that are also attracting attention and investment.

- **Smaller Categories:**

Categories such as **Analytics**, **Automation**, and **Education** have 3 companies each, suggesting that while they are less represented, there is still interest in these areas.

## Conclusion:

The chart illustrates a diverse startup ecosystem with a strong emphasis on SaaS and fintech. The presence of emerging technologies like AI and machine learning indicates significant innovation potential. Investors may consider these categories for future opportunities, as they highlight areas of growth and market demand.

### 7.5.1 Team Size Distribution across Different Categories

---

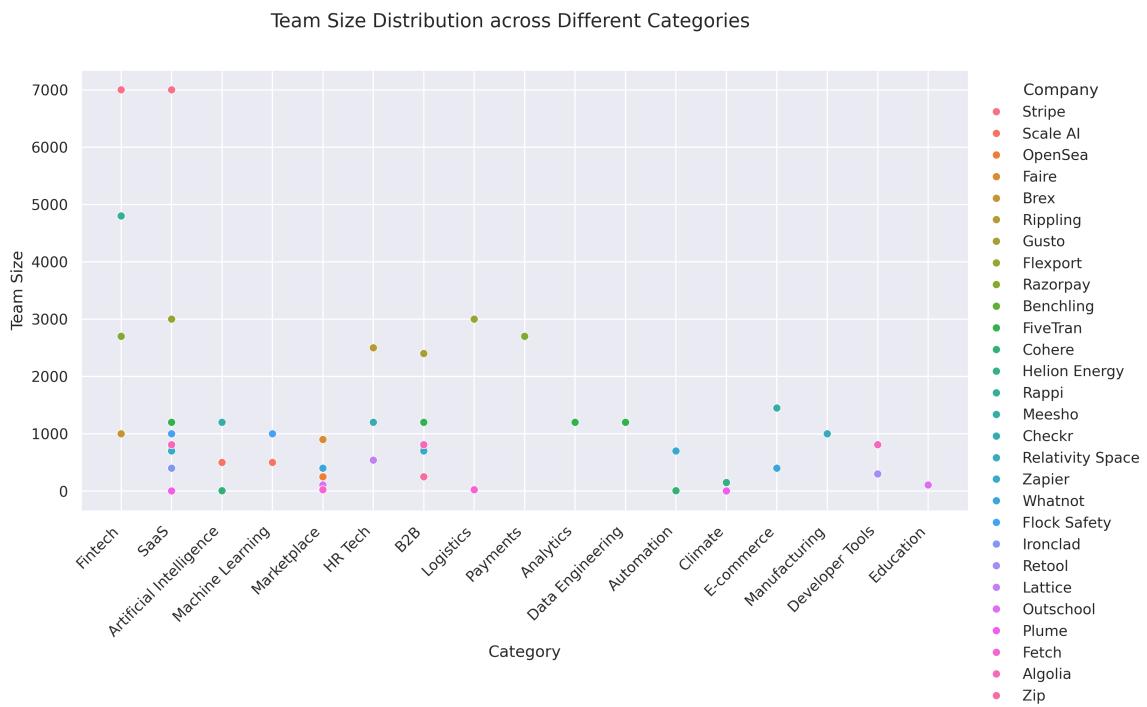
```
_df = df_yc_unicorns.explode('Tags')
_df = _df[_df['Tags'].isin(top_categories['Tags'])]
_df = _df.sort_values(by='Latest Valuation ($B)', ascending=False).head(50)

plt.subplots(figsize=(12,6), dpi=300)
ax = sns.scatterplot(_df, x='Tags', y='Team Size', hue='Company')
```

```

sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1), frameon=False)
ax.set(ylabel='Team Size',
       xlabel='Category')
plt.xticks(rotation=45, ha='right')
plt.suptitle('Team Size Distribution across Different Categories')
plt.show()

```



## Insights:

- **Leading Companies by Team Size:**

**Stripe** has notably large team sizes, reaching close to 7000 employees. This suggests a substantial operational scale, likely driven by their extensive service offerings and market demand.

- **Diverse Team Sizes:**

The chart displays a wide range of team sizes across different categories, indicating that companies in the same sector can vary significantly in scale. For instance, while some fintech and SaaS companies have large teams, others in emerging fields like AI or machine learning may operate with smaller teams.

- **Fintech and SaaS Dominance:**

Categories like **Fintech** and **SaaS** feature prominently among the companies with larger team sizes. This aligns with the need for robust support and development teams in sectors that require continuous innovation and customer service.

- **Smaller Companies in Emerging Categories:**

Companies in categories like **Analytics**, **Education**, and **Developer Tools** tend to have smaller team sizes, suggesting they may be in earlier stages of growth or focusing on niche markets.

- **Potential for Growth:**

The presence of companies with smaller teams in high-potential categories (like AI and machine learning) indicates opportunities for scaling up as market demand increases. Investors may find these companies appealing for future growth prospects.

- **Industry Variability:**

The variability in team sizes within categories suggests that operational strategies and business models can differ significantly, impacting how companies scale and hire.

### **Conclusion:**

The chart highlights the relationship between team size and industry category, showing that larger companies are prevalent in established sectors like fintech and SaaS. In contrast, emerging categories may still have room for growth. This information can guide investors and stakeholders in identifying companies with potential for future expansion and innovation.

## **8 Predictive Analysis**

- **Valuation Predictions:** Use regression models to predict future valuations based on funding and industry factors.
- **Time to Unicorn:** Model the factors influencing the time taken to reach unicorn status.

## **9 References**

- [Unicorn \(finance\) \[wikipedia\]](#)
- [The YC Startup Directory](#)